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# REDUCING LOGISTICS DELAYS USING THE SUPPLY CHAIN CRITICALITY INDEX: A DIAGNOSTIC APPROACH

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# NAVAL POSTGRADUATE SCHOOL

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# THESIS

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by

Owen Lynch

June 2020


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The Department of Navy (DON) struggles with improving logistics delays of parts for systems carried aboard ships. The trend for current logistics improvement efforts has primarily focused on sophisticated stochastic modeling techniques, while low-level performance metrics have yet to be fully leveraged. This research seeks to develop a method for improving logistics delays that can be readily implemented in existing databases and requires no additional software. This research uses a performance metric called the supply chain criticality index to develop a diagnostic approach to identify parts with the highest logistics impact to the system. This method is used in a case study that examines the performance of the Close-In Weapon System (CIWS). The results of this case study agree with reports produced by the Program Executive Office (PEO) of Integrated Warfare Systems (IWS) and further identify new parts for logistics improvement. The proposed method has the promise to significantly reduce logistics delay times for systems carried aboard surface ships and other operational units.

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**REDUCING LOGISTICS DELAYS USING THE SUPPLY CHAIN CRITICALITY INDEX: A DIAGNOSTIC APPROACH**

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Submitted in partial fulfillment of the
requirements for the degree of

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# ABSTRACT

The Department of Navy (DON) struggles with improving logistics delays of parts for systems carried aboard ships. The trend for current logistics improvement efforts has primarily focused on sophisticated stochastic modeling techniques, while low-level performance metrics have yet to be fully leveraged. This research seeks to develop a method for improving logistics delays that can be readily implemented in existing databases and requires no additional software. This research uses a performance metric called the supply chain criticality index to develop a diagnostic approach to identify parts with the highest logistics impact to the system. This method is used in a case study that examines the performance of the Close-In Weapon System (CIWS). The results of this case study agree with reports produced by the Program Executive Office (PEO) of Integrated Warfare Systems (IWS) and further identify new parts for logistics improvement. The proposed method has the promise to significantly reduce logistics delay times for systems carried aboard surface ships and other operational units.

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# List of Acronyms and Abbreviations

**3M** Maintenance Material Management

**AAW** Anti-Air Warfare

$A_a$ achieved availability

$A_i$ inherent availability

$A_o$ operational availability

$A_{o_i}$ individual mission operational availability

$A_{o_{SoS}}$ System of Systems operational availability

**AFIT** Air Force Institute of Technology

**ANOVA** analysis of variance

**ASuW** Anti-Surface Warfare

**C4I** command, control, communications, computers, and intelligence

**CASREP** Casualty Report

**CDMD-OA** Configuration Data Managers Database-Open Architecture

**CIWS** Close-In Weapon System

**CNO** Chief of Naval Operations

**CNRM** Commander, Navy Regional Maintenance

**CNSP** Commander, Naval Surface Forces Pacific

**COA** course of action

**COTS** commercial off-the-shelf

| | |
|---|---|
| **DAG** | Defense Acquisition Guide |
| **DF** | Demand Factor |
| **DOD** | Department of Defense |
| **DON** | Department of Navy |
| **eDFS** | electronic departure from specification |
| **EDO** | engineering duty officer |
| **eLog** | electronic log application |
| **FOC** | Full Operational Capability |
| **FOUO** | For Official Use Only |
| **GAO** | Government Accountability Office |
| **HME** | hull, mechanical, or electrical |
| **INCOSE** | International Council on Systems Engineering |
| **INSURV** | Inspection and Survey |
| **ITSM** | Information Technology Service Management |
| **IWS** | Integrated Warfare Systems |
| **JCIDS** | Joint Capability Integration and Development System |
| **JCN** | Job Control Number |
| **KPP** | key performance parameter |
| **MAdmT** | mean administrative time |
| **MAdmDT** | mean administrative delay time |
| **MDT** | mean down time |
| **MGTIS** | Marine Gas Turbine Information System |

**MFOM** maintenance figure of merit

**MLDT** mean logistics delay time

**MLT** mean logistics time

**MOAT** mean outside assist time

**MOADT** mean outside assist delay time

**MOE** measure of effectiveness

**MOP** measure of performance

**MOS** measure of suitability

**MRDB** Material Readiness Database

**MSRT** mean supply response time

**MTBF** mean time between failure

**MTTR** mean time to repair

**MS** Microsoft

**NAVSEA** Naval Sea Systems Command

**NDE** Navy Data Environment

**NMD-R** Navy Maintenance Database-Platform

**NoB** Not on-Board

**NPS** Naval Postgraduate School

**NVR** naval vessel register

**NSLC** Naval Sea Logistics Center

**NIIN** national item identification number

**NMCI** Navy and Marine Corps Intranet

**NSN** NATO stock number

**NSWC** Naval Surface Warfare Center

**OPNAVINST** Office of Chief of Naval Operations Instruction

**PEO** Program Executive Office

**POC** proof(s) of concept

**RBD** reliability block diagram

**RMA** reliability, maintainability, and availability

**RSN** record serial number

**SAMMS** Shipboard Automated Management Maintenance Systems

**SATCOM** satellite communications

**SE** systems engineering

**SCCI** supply chain criticality index

**SCM** supply chain management

**SOI** system of interest

**SoS** system of systems

**STAT** Scientific Test and Analysis Techniques

**SURFMEPP** Surface Maintenance Engineering Planning Program

**TAAS-INFO** Tech Assist, Assessments and Scheduling Information

**TAVR** Technical Assistance Visit Report

**TSRA** Total Ship Readiness Assessment

**TYCOM** Type Commander

**UHF** ultra high frequency

**USN** U.S. Navy

**VPN** virtual private network

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# Executive Summary

The Department of Navy (DON) needs greater capability in diagnosing reliability, maintainability, and availability (RMA) problems for weapon systems carried aboard operational units [1]. One of the ways the DON assesses system readiness is by measuring the operational availability ($A_o$). Logistics delays are a significant problem associated with system performance and operational availability ($A_o$). The Program Executive Office (PEO) for the DON continuously works to improve the system performance of their programs. The PEO Integrated Warfare Systems (IWS) requested assistance from the Systems Engineering Department at Naval Postgraduate School (NPS) in developing an analytical strategy to improve the performance of the Phalanx CIWS system by reducing the logistic delay contributions to downtime.

This research finds that accessible and accurate logistics delay analysis is achievable using low-level supply chain performance metric calculations. In addition, this analysis does not require specialized software, and system performance databases already calculate the requisite uptime and downtime metrics.

A general definition of availability is the ratio of uptime to the total time that the system should have been available. Uptime $T_{up}$ is the total amount of time the system was available to operate over a chosen time interval, and downtime $T_{down}$ is the total amount of time a system was unavailable. Total Time $T_{total}$ is the sum of uptime and downtime [2, p. 5]. Equation 1 defines availability as

$$A = \frac{T_{up}}{T_{up} + T_{down}} = \frac{T_{up}}{T_{total}}. \tag{1}$$

The *Operational Availability Handbook* defines $A_o$ as Equation 2,

$$A_o = \frac{MTBF}{MTBF + MTTR + MLDT}. \tag{2}$$

Each term in Equation 2 is defined here [3].

- mean time between failure (MTBF) := The average time between failures.
- mean time to repair (MTTR) := The average time elapsed for corrective maintenance.
- mean logistics delay time (MLDT) := The average time a system is unavailable due to logistics system delays associated with all maintenance actions.

## Optimization Model

The original need statement from the PEO was for an optimization model capable of using existing performance data and determine the change in overall system availability, given a change in overall logistics delay. As software accessibility issues within the PEOs require the use of Microsoft (MS) Excel [4], such an optimization model could be used by program managers to form the basis for a cost-benefit analysis and make informed decisions on program budget allocation. Additionally, a generalized optimization method capability can apply to other systems within the DON with similar data tracking features. The author determined that a low-level availability optimization for this system was infeasible. Further, in exploring the feasibility of an optimization model, the author documented why an optimization could not be accomplished and determined.

Historical data on the Close-In Weapon System (CIWS) Block 1B from the MRDB validates the proof(s) of concept (POC) in this research. System data from the MRDB is unclassified controlled information, For Official Use Only (FOUO), distribution statement D. A more detailed analysis is provided in the Supplemental Case Study, which can be accessed by contacting the NPS Dudley Knox Library.

The following list summarizes the observations from the optimization model POC:

1. **Optimization Documentation:** Previous $A_o$ optimization projects with similar goals have taken place. However, interviews with stakeholders resulted in no documented research or results. Therefore this work was not built on or referenced in this thesis.
2. **MRDB Accessibility:** The MRDB-NG is a web-based application that is only accessible via the Navy and Marine Corps Intranet (NMCI). However, challenges to establishing any connection to the NMCI resulted in the MRDB exporting data into MS Excel format.
3. **Data Validity in MS Excel:** Ghost artifacts, missing data entries, and illogical data entries invalidate the exported MS Excel formatted performance data. Direct access

to the MRDB web browser is required to assess the most accurate performance data.

4. **System of Systems Complexity:** Interdependencies between parts and subsystems require stochastic processes to calculate overall $A_o$ and other performance metrics. A low-level optimization model is not capable of calculating an overall system $A_o$ as a result of changes to individual part MLDTs. If it were feasible to create such a model, this result would replicate what is currently being performed by the MRDB.
5. **Part Cost Variance:** The cost of replacement parts has high variance and does not trend, resulting in an inherent error in a cost-benefit analysis that uses this optimization model. Cost data shows that replacement part costs greatly increase and decrease each fiscal year.
6. $A_o$ **Factor Variance:** Noticeable variance in MTBF and MLDT result in a high uncertainty in the effect of changing individual part MLDTs. Unpredictable reliability and logistics factors likely dominate a marginal reduction in overall system MLDT.

## Logistics Reduction Analysis Method

Using the observations of the optimization model POC and the supply chain criticality index (SCCI), a diagnostic method is developed in this research to improve the overall MLDT for systems of interest (SOIs). This method is validated by conducting a case study using CIWS performance data and comparing the method's results with RMA results from PEO reports. Figure 1 gives an illustration of the generalized method.

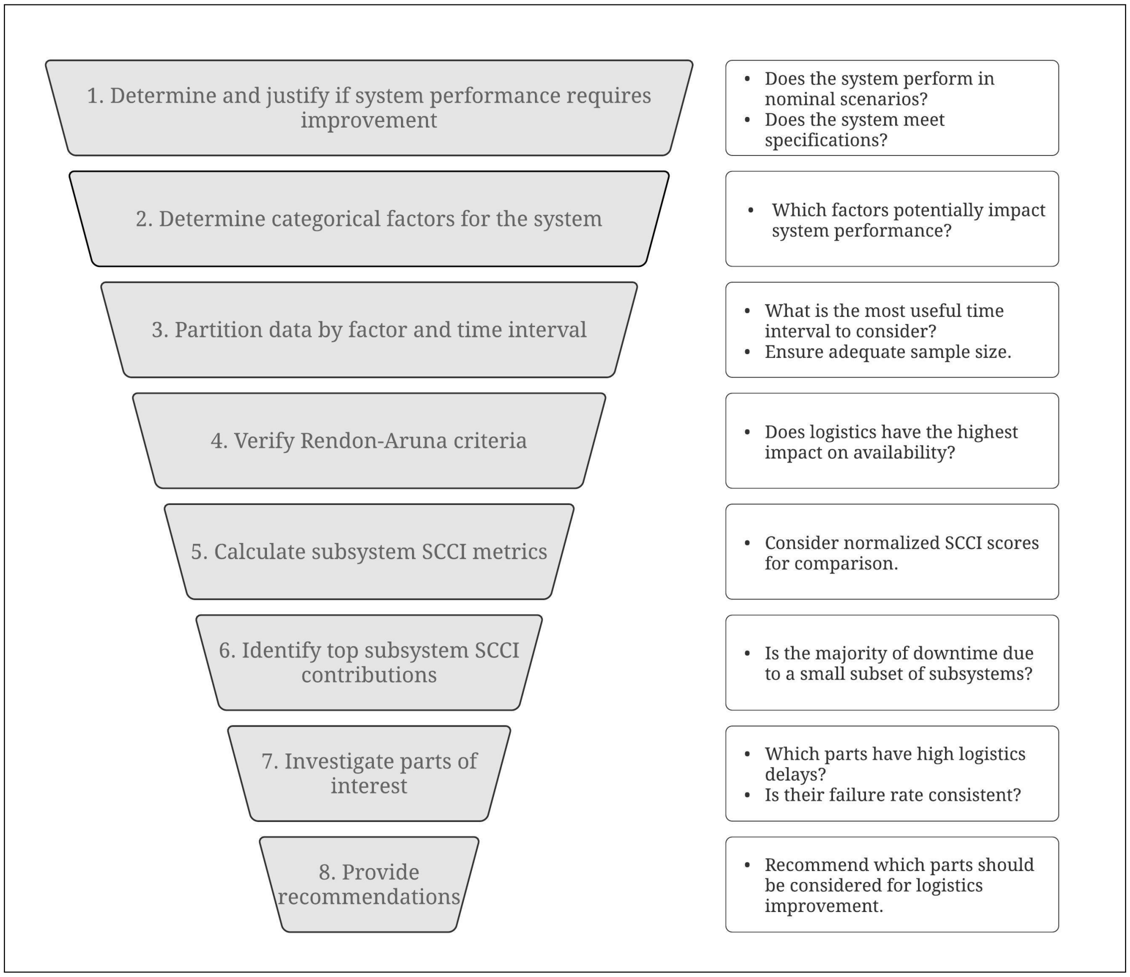


Figure 1. Method developed in this research to Improve Logistics Delays Using the SCCI performance metric. The first step of the method is at the top of the figure and sequentially moves down. Key considerations and questions relevant to each step are to the right of each step.

Figure 1 shows a sequence of analysis steps for efficiently diagnosing logistics delay problems. In general, stakeholders assess system data at the fleet level, where every operational system is pooled together for analysis. In general, little has been done to explore categorical factors and their importance on $A_o$ and MLDT. Additionally, weapon system stakeholders place too much emphasis on $A_o$ to assess readiness [5]. System availability is a time-independent ratio that cannot assess how well a system performs a mission. The method shown in Figure 1 accounts for system readiness and categorical factor considerations. Additionally, steps one and four of Figure 1 are justification steps, preventing irrational analysis from occurring. Step four utilizes research from Rendon and Aruna [6], which shows that, under typical Navy system $A_o$ conditions, MLDT has higher elasticity than MTBF or MTTR with respect to $A_o$. These system conditions include the following criteria:

1. System $A_o$ is normally above 0.50 or 50%.
2. $MTBF > MTTR + MLDT$
3. $MLDT > MTTR$

If the Rendon-Aruna criteria given in [6] is satisfied, then reducing the overall system MLDT has a greater impact compared to increasing the overall system MTBF.

This method is a hierarchical approach, starting at the overall system level, analyzing down to the subsystem and parts levels. The method identifies the top contributing subsystems to logistics delays. It then investigates the cause at the parts level, resulting in potential parts for consideration in placing them on-board operational units.

The SCCI used in steps five and six of Figure 1 is a measure to determine which component within a SOI is most likely to be ordered as a result of a failure event [7]. The SCCI is defined in [7] as

$$SCCI_i = N_i * \lambda_i * MLDT_i. \tag{3}$$

- $N_i$ **:=** The total number of that unique part required for the SOI to operate.
- $\lambda_i$ **:=** The failure rate of the *ith* component in the SOI.
- $MLDT_i$ **:=** The mean logistics delay time (MLDT) of the *ith* component in the SOI.

Equation 3 shows that SCCI increases with the number required, the failure rate, and the mean logistics delay. Normalizing SCCI calculations result in the percent contribution to the overall MLDT. The same SCCI analysis can use subsystem level data as well.

## CIWS Case Study and Findings

This case study considered CIWS Block 1B performance data from FY14 to FY19, with performance data grouped by fiscal year and homeport. The diagnostic method given in Figure 1 made the following conclusions:

- **Readiness:** The CIWS outperforms documented MTBF requirements and underperforms in nominal mission scenarios. Reliability requirements do not include threshold and objective criteria. Notably, CIWS readiness depends on which criteria is used to conduct the assessment. The CIWS is unready in the operating environment, and stated specifications do not reflect this assertion.

- **Rendon-Aruna Criteria:** The performance data satisfies the Rendon-Aruna criteria, concluding that MLDT has a higher elasticity than MTBF.
- **Subsystem Contributors:** The top five contributing subsystems to SCCI make up at least 75% of logistics delays for each fiscal year considered. The method shows that focusing on a small subset of subsystems captures the majority of logistics delays. Frequency analysis of the top contributing subsystems identifies six subsystems for further investigation.
- **Parts of Interest:** Investigating these six subsystems results in seventeen parts of interest. Of the seventeen initially identified, six parts are potential candidates to be on-board replacement parts.
- **Comparison to RMA Reports:** The parts of interest identified in the diagnostic method included all parts identified as top supportability drivers. Additionally, this diagnostic method shows that PEO logistics initiatives have been effective in reducing overall logistics delays.
- **Minimum MLDT:** The case study suggests that the number of potential logistics improvement solutions is decreasing, resulting in the majority of logistics delays occurring due to unpredictable failures. This observation suggests that there is a minimum overall MLDT asymptote that the program is approaching. Further efforts to improve overall $A_o$ should focus on areas of downtime that are more easily changed, such as mean administrative delay time (MAdmDT) or reliability improvements.

The diagnostic method, given in Figure 1, applies to any system tracked by the MRDB and is generally applicable to other DON systems with databases that calculate standard performance metrics. Additionally, the iterative application of this method to the same system results in the progressive improvement of logistics delays and diagnoses drivers for system readiness.

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# CHAPTER 1: Introduction

One of the ways the Department of Navy (DON) assesses system readiness is by measuring operational availability. A significant problem associated with system performance and operational availability is logistics delays. Contributions to downtime in a system result in an increased portion of time that the system is unavailable. Factors that contribute to downtime include unexpected or unplanned delays in parts availability, arrival times, maintenance equipment availability, and shipping times. The Program Executive Office (PEO) for the DON continuously works to improve the system performance of their constituent programs. The PEO Integrated Warfare Systems (IWS) requested assistance from the Systems Engineering Department at Naval Postgraduate School (NPS) in developing an analytical strategy to improve the performance of the Phalanx CIWS system by reducing the logistic delay contributions to downtime. Many factors contribute to the downtime of a system, and the PEO asked for assistance in specifically improving the logistics delay.

The original need statement from the PEO was for an optimization model capable of using existing performance data and determine the change in overall system availability, given a change in overall logistics delay. Software accessibility issues within the PEOs require the use of Microsoft (MS) Excel. Such an optimization model could be used by program managers to form the basis for a cost-benefit analysis and make informed decisions on program budget allocation. Additionally, building an optimization method could apply to other systems within the DON with similar data tracking features.

## 1.1 Background

This section introduces background information relating to this thesis. Understanding the background information is important for understanding this research. A detailed background review is given in Chapter 2. This thesis primarily resides in three fields: Acquisitions and Life-Cycle Management, systems engineering (SE), and Data Analysis. DON systems live within acquisitions and life-cycle management. One specific process that governs how programs move from one milestone decision to another is the Joint Capability Integration and Development System (JCIDS), as illustrated by Figure 1.1.

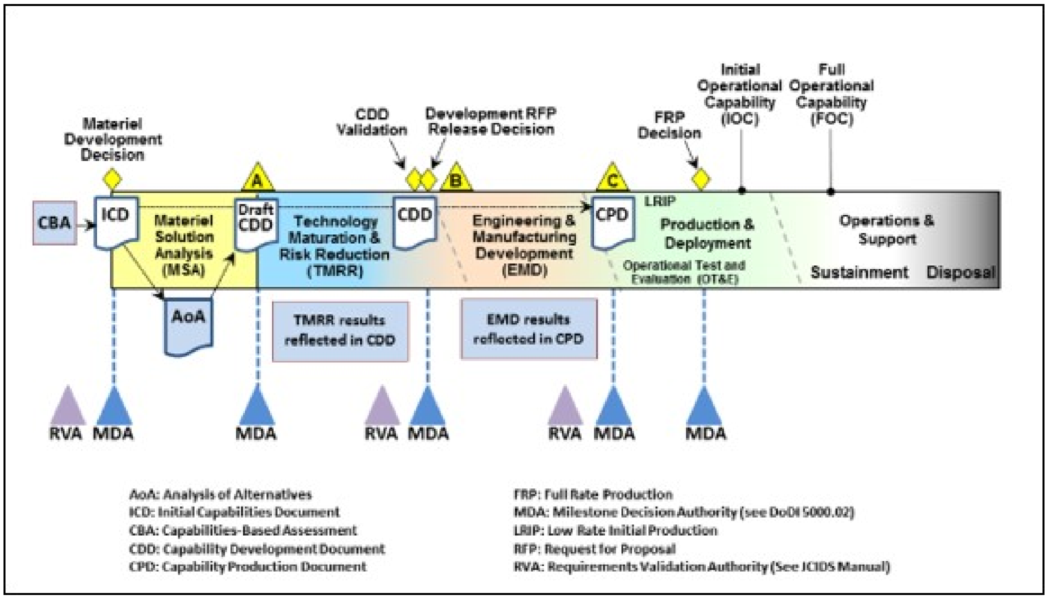


Figure 1.1. JCIDS Process Overview. Source: [1].

Figure 1.1 is an illustration of the key milestones and events a Department of Defense (DOD) system of interest (SOI). This research is primarily interested in SOIs that has reached Full Operational Capability (FOC) and is in the operation and support phase. Figure 1.1, on the far right, shows the operation and support phase of the JCIDS process. In this phase of the life-cycle of a SOI, the majority of annual program costs rest in maintaining operational systems. Blanchard and Fabrycky [2, p. 34] give examples of activities associated with the operation and support phase that include the following:

- maintenance support
- logistics support
- incremental system modifications
- contractor support
- system performance data collection

The second general area of this thesis is systems engineering (SE). SE concepts and practices provide this thesis with a logical and structured approach to defining a problem and arguing a solution. Section 1.6.2 provides a detailed explanation of how this thesis uses SE concepts. The third general area this research is associated with is data analysis, focusing on statistics and optimization models. Data analysis is the general process of discovering useful information from a set of data. Chapter 3 detail the use of data analysis in this research.

## 1.2 Problem Statement

The primary research question is the following:

1. Operational availability is the primary metric for assessing system readiness in the DON. Is it feasible to construct a low-level optimization model that reduces logistics downtime and increases the overall $A_o$ of a system?

Secondary questions in support of the primary research question are the following:

1. If a low-level optimization model is infeasible, is there another supply chain performance metric that can be readily implemented that reduces logistics downtime of a system?
2. What conditions are necessary to implement such a performance metric?

## 1.3 Benefit of Study

The benefit of this study is to attempt to find more meaningful methods to assess system performance within the DON. Systems carried aboard operational units can never be directly tested during deployment while remaining available. To ensure that we, as a military, have an adequate level of force, measures of performance are created for systems to determine readiness. Since direct testing of weapon systems is infeasible, proxy measures are required to determine readiness level. These performance metrics allow for informed decisions on how to change aspects of the system. This thesis specifically focuses on improving logistics support by implementing analysis techniques and metrics.

PEOs report on the availability of their systems. A system's availability is a proxy measure for how ready it is to perform its intended function. An assessment of how the DON uses performance metrics is critical to providing program managers with tools that can give them more useful information for supporting their systems.

## 1.4 Limitations and Assumptions

This section establishes the space in which the research is valid, explicitly stating limitations and assumptions so that the reader understands the context in which this research answers the primary and secondary research questions.

### 1.4.1 Limitations

This research focuses on performance metrics used by the acDON to assess readiness and systems that are tracked by the Material Readiness Database (MRDB). The MRDB maintains failure and maintenance data on over 300 critical navy systems, including the Phalanx Close-In Weapon System (CIWS). These systems are at FOC and are considered critical systems. Recall that Figure 1.1 illustrates the major phases of a SOI life-cycle. This thesis limits the systems under research to those tracked under the MRDB. This research does not focus on DOD systems that have not reached full production.

To assess systems with consistent data, this research only considers systems tracked by the MRDB. Within the space of system performance data in the DOD, the MRDB is a subset of Naval Sea Systems Command (NAVSEA) within the DON. The MRDB is the only comprehensive system performance database within the DON that track many different kinds of systems. Even though this thesis has focused on systems tracked by the MRDB, a generalized method of analysis that works for one system is easily transferable to other systems due to data compatibility.

This research limits the kinds of systems being assessed to those within the DON due to professional background. The author is a submarine officer within the DON with a broad and necessary background in the DON's command structure that governs program management. Additionally, the author has professional experience with managing large systems in the operation and support phase within the submarine force. This thesis does not consider systems operated by other service branches due to the author's background and the DON's PEO interests.

Additionally, this research is interested in applying performance metrics to performance data that is currently available. This research is not interested in performance metrics which are either slow to implement or are impractical due to data deficiencies. Deficiencies in data tracking and collection are left for future work.

### 1.4.2 Assumptions

This subsection briefly explains the necessary assumptions for this research to occur. There are several analysis techniques described in this thesis that contain their own assumptions. Those specific instances of assumptions are described later in the thesis.

#### Performance Data Accuracy

The most necessary assumption to make in this research is that performance data is as accurate as possible. Recording system performance is never perfect, and databases contain missing information and errors. This thesis documents irregularities in performance data; however, the research must assume that the given performance data is accurate.

## 1.5 Research Objectives

This section explains each objective and how they contribute to answering the primary and secondary research questions. The following list gives the research objectives for this thesis.

1. Provide the reader with the necessary background and awareness of current research to understand the thesis arguments.
2. Determine the feasibility of an optimization model for the Phalanx CIWS system based on the needs statement from PEO IWS.
3. If an optimization model is infeasible, this research will research and develop a methodology for reducing logistics delay times for systems.
4. Perform a case study on either the established methodology or optimization model using system performance data from the MRDB.
5. Provide recommendations for how system performance metrics should be used within the DON.

### 1.5.1 Objective 1

Objective 1 is addressed in Chapter 2 and reviews key concepts on performance metrics, reliability theory, DOD system management, and data management. This objective serves to explain the necessary information so that the research can be understood and to establish a common language. Key concepts associated with this objective include the following topics:

1. Availability

2. Reliability theory
3. Markov analysis
4. The stakeholders associated with system management and sustainment within the DON
5. The Material Readiness Database (MRDB) and how it functions

Objective 1 provides an adequate literature review on supply chain performance metrics. This review is necessary to provide the reader with a common language and understanding of topics necessary to understand for the research.

### 1.5.2 Objective 2

Objective 2 is addressed in Chapter 3. This objective is fundamental to answering the primary research question of this thesis. If this research can determine the feasibility of building an optimization model, then the direction of research turns in one of two directions. If an optimization model is feasible, then this research continues in developing the model for the PEO stakeholders. If the model is not feasible, then the research analyzes why the model did not work and what methodology could serve to reduce logistics delay times.

SE practices apply to the optimization model and methodology. This thesis determines the feasibility of need statements based on logical applications of SE.

### 1.5.3 Objective 3

Objective 3 is addressed in Chapter 4. This objective helps to answer the secondary research questions. If this research finds that an optimization model is infeasible, then the research must explore and develop alternate strategies for diagnosing logistics delays in large DON systems. If a methodology is feasible, then program managers can use it to analyze the logistics delay portion of system downtime. Improving logistics downtime would then improve the overall system availability.

### 1.5.4 Objective 4

This objective validates the process for reducing logistics delay time for DON systems. This objective provides evidence to the reader that the method functions correctly with actual performance data. This objective also serves as a guide for how program managers can perform the same analysis on their respective systems. The selected SOI for this case study is the Phalanx CIWS Block 1B weapon system. Naval Surface Warfare Center (NSWC) Corona and the Material Readiness Database (MRDB) provide system performance data used to conduct this case study. The supplemental case study documents Objective 4 and validates the logistics delay improvement process. Performance data from the MRDB is unclassified controlled information. Access to the supplemental case study is through the NPS Dudley Knox Library.

### 1.5.5 Objective 5

Objective 5 is addressed in Chapters 3 and 4 and summarized in Chapter 5. This research documents how stakeholders use performance metrics and compare those practices to what governing documents and current research suggest. Chapter 5 documents these observations in a concise summary of recommendations and observations. Objective 5 provides amplifying guidance to the primary and secondary research questions of this thesis. Chapter 4 provides a detailed context for the proper applications of an optimization model or methodology.

## 1.6 Research Methodology

This section discusses the type of research included in this thesis and explains the SE applications to the research.

### 1.6.1 Research Type

This research is an *analysis thesis*. Statistics and numerical analysis techniques are used in conjunction with established risk engineering theories to develop a methodology for improving logistics delay times of DON systems. This research also includes a case study using actual system performance data obtained from the MRDB.

### 1.6.2 Systems Engineering Practices

This research uses portions of the SE "V-model" in addition to SE practices to accomplish the objectives stated in Section 1.5. Figure 1.2 gives an example of the SE V-model.

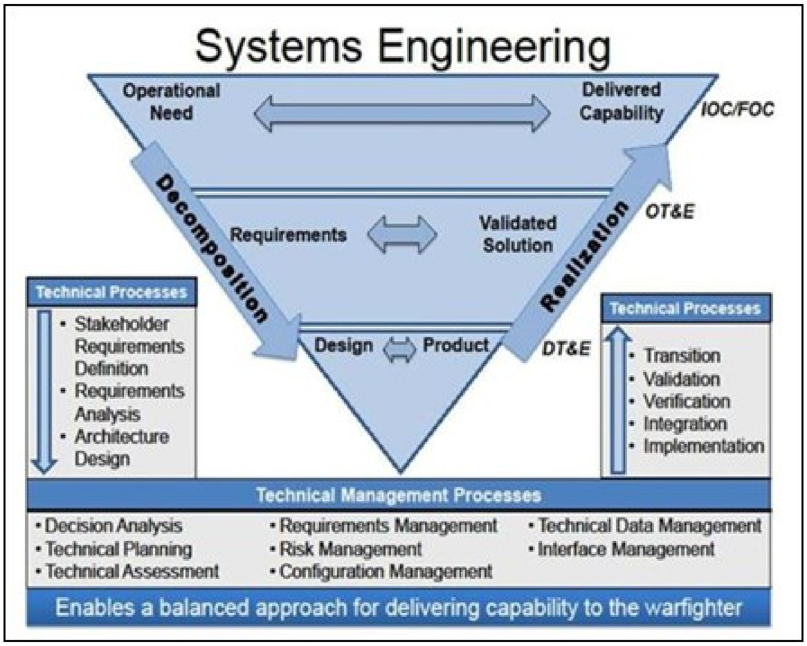


Figure 1.2. SE V-Model Process Diagram. Source: [1]. The v-model starts at the top left of the figure with needs analysis and follows the arrows. Lateral arrows indicates feedback between initial and final SE processes.

Figure 1.2 gives a graphical description of how to start with an operational need and produce an operational capability that meets the need. Initial problem definition, capability development, requirements generation, etc. must be performed to provide stakeholders with a well defined and communicated problem statement. Stakeholder analysis is essential when developing a product or methodology. There are many stakeholders associated with DON systems tracked by the MRDB. It is important to understand the needs and priorities of the stakeholders to identify capability gaps.

The analytical approach developed as part of this thesis is applied to the CIWS system as a case study. This case study serves as the validation method in Figure 1.2. The case study also serves as a validation for similar systems tracked by the MRDB. This thesis does not progress to the operational capability phase of Figure 1.2. This research is primarily concerned with developing a validated method that addresses the operational need.

### 1.6.3 Systems Engineering Employment

**Initial Problem Statement and Capability Gaps**

Part of SE's goal is to ensure that a system or method satisfies a need based on current deficiencies. The initial problem statement is a claim that a SOI is lacking in specific capabilities. The set of missing capabilities that the SOI should have is what makes up to the set of capability gaps. The initial problem statement is synonymous with the operational need shown in Figure 1.2.

**Functional Decomposition**

Capabilities are met or executed by accomplishing functions. The act of decomposing capabilities into cognizant functions, known as functional decomposition, turns capability statements into active statements.

**Requirements**

System requirements are a byproduct of functional decomposition and an exploration of the capabilities that the SOI should provide. System requirements should satisfy general attributes that make them "good" requirements. SE publications summarize these attributes into SMART criteria. Publications have not come to a consensus on what the acronym exactly stands for. This thesis takes SMART from Mannion and Keepence [3] to mean the following:

- Specific: The requirement is a single condition the system must satisfy. If the requirement includes multiple conditions, then those conditions are separated into multiple requirements.
- Measurable: The question of whether the requirement is met or not shall be tied to a quantifiable result. The requirement could be binary (yes/no) or any number of measurable units. The form of measurement should be specific. For example, if a requirement for a car states that the system shall weigh no more than 500 units, it makes a considerable difference if the vehicle is being weighed in tons, long-tons, kilograms, pounds, stone, etc.
- Achievable: The requirement should be realistic, meaning that the requirement should be technically feasible and within the realm of possibility to accomplish.

- Relevant: The requirement should be relevant to the system.
- Time-Bound: The requirement should be constrained to be accomplished within a specific period.

**Feedback**

SE process diagrams yield varying levels of feedback. In general, as engineers find problems with capabilities, requirements, functions, and design implementation, they should trace the problems through the SE process to improve the system design. Making changes to the system must trigger feedback mechanisms to check that the system is still achievable. Often, components have interfaces between other components within a system. Changing one interface may impact a different interface.

**Performance Metrics and Validation**

Feedback and validation are always present in the SE vee-model shown in Figure 1.2. System performance is measured to validate system success. In SE, **measure of effectiveness (MOE)** is defined as "the operational measures of success that are closely related to the achievement of the mission or operational objective being evaluated, in the intended operational environment under a specified set of conditions; i.e., how well the solution achieves the intended purpose" [4, Ch. 5, Sec. 7]. MOEs usually cannot be measured directly. As a result, MOEs are indirect measurements, represented by one or more **measure of performance (MOP)**. A measure of performance (MOP) is "the measure that characterizes physical or functional attributes relating to the system operation, measured or estimated under specified testing and/or operational environment conditions" [4, Ch. 5, Sec. 7].

There can be a special subset of MOPs that are deemed especially critical to system performance. This subset of measures is **key performance parameters (KPPs)**. KPPs are "a critical subset of the performance parameters representing those capabilities and characteristics so significant that failure to meet the threshold value of performance can be cause for concept, or system selected to be reevaluated or the project to be reassessed, or terminated" [4, Ch. 5, Sec 7]. Each KPP should have a threshold and objective value. The threshold value is the minimum performance the SOI must attain, while the objective value is a target goal.

**Performance metrics** are more general than the subsets of KPPs and MOPs. Performance metrics are simply measures that relate to the performance of a SOI. Performance metrics do not necessarily have threshold and objective requirements attached to them.

## 1.7 Chapter Summary

This chapter discussed the problem statement, objectives, and boundaries of this thesis. The remaining chapters of this thesis explore the requisite background information, current research, and research conducted by the thesis. Chapter 2 provides the necessary background and literature review. The background portion of Chapter 2 provides the necessary information and references to understand this thesis. The literature review portion of Chapter 2 establishes the necessary definitions and models currently used to assess system readiness. Additionally, Chapter 2 gives insights into other research on the subjects of availability and techniques for determining system performance. Chapter 3 is a detailed account of the attempt to build an optimization model for PEO IWS. Chapter 3 describes the analytical methods used for assessing system performance. Chapter 3 documents all challenges in building an optimization model, reviewing each model assumption, and making observations on the feasibility of building an optimization model. Using the conclusions obtained in Chapter 3, the thesis develops a methodology for reducing logistics delay time in Chapter 4 that includes low-level calculations. Chapter 4 explains the preferred processes and considerations for conducting logistics delay improvement studies. Chapter 5 provides conclusions of this research and recommendations for areas of further study. The supplemental case study of this thesis is a case study of the methodology developed in Chapter 4 applied to the Phalanx 1B weapon system. The case study uses actual system performance data obtained from NSWC Corona Division to show how this methodology performs on real system data. The supplement is unclassified controlled information, FOUO, distribution statement D. Requests for the supplement should be directed to the NPS Dudley Knox Library.

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# CHAPTER 2:
# Background and Literature Review

This literature review chapter has two sections: **Background** and **Current Research**. This chapter discusses the necessary background to understand performance metrics and the stakeholders associated with performance metrics within the DON. This chapter also discusses current research around DON performance metrics and performance metric improving methodologies. The conclusion of this chapter explains how this research fits within the field of SE, system life-cycle management, and data analysis.

## 2.1 Background

This section discusses the necessary background information and theories to understand the research given in subsequent chapters. The intent of this section is to provide a base level of understanding for the reader to follow the work that is done in this thesis. This section introduces concepts relating to performance metrics, availability, reliability, and Markov processes. This section goes further to describe the stakeholders involved with tracking system performance data and the MRDB.

### 2.1.1 Why Performance Metrics

Performance metrics are a powerful tools for program managers. Straight [5] argues that it is necessary to assess system efficiency and effectiveness with measurement. Within the DOD, readiness is a complex measure for large weapon systems. Performance metrics are a representation of what real-world system performance is. Fortunately, most DOD weapon systems are not used to their designed capability in a peacetime environment. This lack of user experience requires program owners to assess the readiness of the system using indirect measures. Indirect measures are a representation of the system's likeliness to work. Major programs within the DON are budgeted for many millions of dollars each fiscal year as shown by [6]. With large program budgets at stake, it is important to ensure money is spent effectively.

These performance metrics attempt to accomplish two tasks. The first task is to provide supporting evidence that a system will work when needed. The second task of performance metrics is to suggest when a system requires redesign. Availability is the DOD's primary measure to assess system readiness. Availability is the probability that a system will function correctly when the user attempts to operate the system.

### 2.1.2 Performance Metric Definitions

Table 2.1 is a consolidated list of terms, their corresponding acronym, and definition with a source citation. Table 2.1 establishes common definitions for commonly used terms. Unfortunately, this research has found variations in definitions for the same terms. The *MRDB User Manual* and DON's *Operational Availability Handbook* [7], [8] were used to establish common definitions for this research.

Table 2.1. Availability Key Terms and Definitions. Source: [7], [8].

| Term and Symbol | Definition |
|---|---|
| mean down time (MDT) | "The average time a system is unavailable for use due to either corrective or preventative maintenance" [7]. |
| mean logistics delay time (MLDT) | "The average time a system is unavailable due to logistics system delays associated with all maintenance actions" [7]. |
| mean administrative time (MAdmT) | "The average period of down time awaiting resources, other than spare parts and outside assistance, when such delays exist" [7]. |
| mean administrative delay time (MAdmDT) | "Mean Administrative Delay Time is the average period of down time awaiting resources other than spare parts. It includes time awaiting qualified [on board] maintenance personnel, support equipment, technical data, training, facilities, etc" [7]. |
| mean outside assist delay time (MOADT) | "The average period of down time awaiting maintenance teams from other locations-depot repair teams and general support teams who travel to operating sites to perform maintenance are examples" [7]. |
| mean outside assist time (MOAT) | "The average period of down time awaiting maintenance teams from other locations when they are required" [7]. |
| mean time between failure (MTBF) | "The average time between failures, which causes a loss of a system function, considered critical by a customer" [7]. |
| mean time to repair (MTTR) | "The average elapsed time for corrective maintenance (including testing times for fault detection, isolation, and verification of correction)" [7]. |
| mean supply response time (MSRT) | "The average time an item is unavailable due to waiting for hardware sources thru the supply system. It is measured from the time the part requisition is entered until the part is issued from supply, and includes on-board and off-board delays. It includes time waiting for approved parts, tools, support and test equipment, etc" [8]. |

### 2.1.3 Availability

Availability in DOD systems management is the ratio of time that a system is available to be used over the amount of time the system should have been available. A general definition of availability is the ratio of uptime to total time that the system should have been available. Uptime $T_{up}$ is the total amount of time the system was available to operate over a period of interest. Downtime $T_{down}$ is the total amount of time a system was unavailable to operate over a period of interest. Total Time $T_{total}$ is the sum of uptime and downtime [8, p. 5]. Equation 2.1 defines the availability as

$$A = \frac{T_{up}}{T_{up} + T_{down}} = \frac{T_{up}}{T_{total}}. \tag{2.1}$$

System uptime and system downtime can be counted in several different ways. How uptime and downtime get counted depends on the data collection process for the system. This variation in counting uptime and downtime makes understanding their definitions crucial to understand. Figure 2.1 is an illustration of how uptime and downtime are further decomposed into different categories.

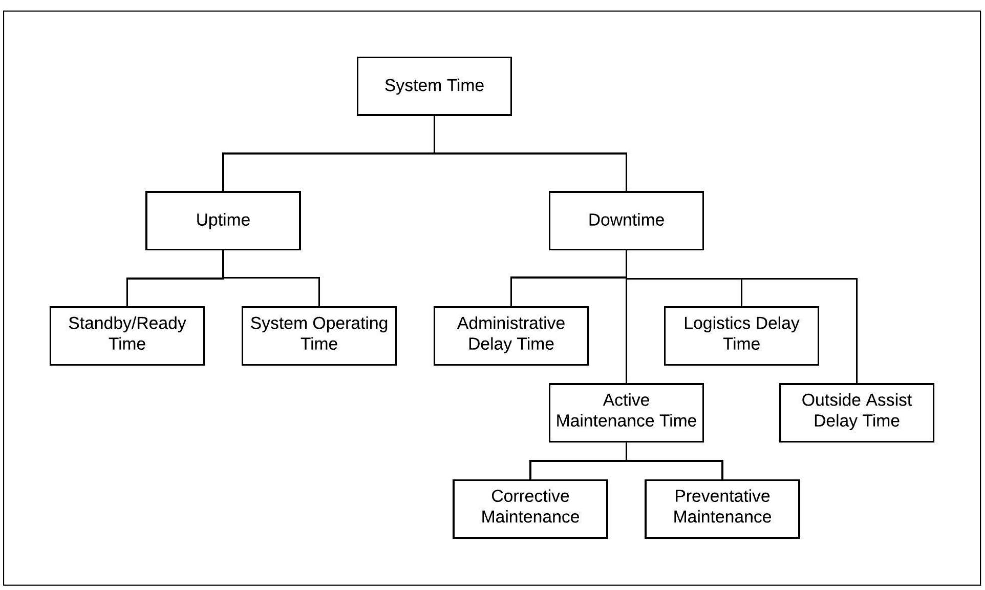


Figure 2.1. Contributions to System Time. Adapted from [2, p. 422].

Figure 2.1 shows how uptime and downtime of a SOI can be decomposed. Uptime is relatively simple. If a SOI is up, then it is either not in operation and in standby, or it is in operation. Downtime can be decomposed into many unique subcategories. These different subcategories help explain why a system is down and where time is lost. It is clear to say that as downtime increases, SOI availability decreases. As downtime is defined in different ways, the definition for system availability fundamentally changes. There are three main definitions of availability, and they are unique from one another in terms of how downtime $T_{down}$ is defined.

Inherent availability ($A_i$) is "the probability that a system or equipment, when used under stated conditions in an ideal support environment, will operate satisfactorily at any point in time as required" [2, pp. 492-493] and is given by Equation 2.2:

$$A_i = \frac{MTBF}{MTBF + MTTR}. \tag{2.2}$$

Achieved availability ($A_a$) is "the probability that a system or equipment, when used under stated conditions in an ideal support environment, will operate satisfactorily at any point in time" [2, pp. 492-493]. This form of availability is defined as

$$A_a = \frac{MTBM}{MTBM + \bar{M}}. \tag{2.3}$$

Achieved availability includes preventative maintenance in downtime while inherent availability does not. This difference implies that MDT is greater than MTTR. It follows that, for the same system, achieved availability is always less than or equal to inherent availability ($A_i$). Operational availability ($A_o$) is "the probability that a system or equipment, when used under stated conditions in an actual operational environment, will satisfactorily operate when called upon" [2, pp. 492-493]. Blanchard and Fabrycky and the Navy's *Operational Availability Handbook* define $A_o$ as

$$A_o = \frac{MTBF}{MTBF + MTTR + MLDT}. \tag{2.4}$$

The Navy's *Operational Availability Handbook* gives an alternate definition of $A_o$, decomposing MLDT into its constituent parts. That is,

$$MLDT = MSRT + MOADT + MAdmDT. \tag{2.5}$$

Equations 2.4 and 2.5 are combined to produce equation 2.6:

$$A_o = \frac{MTBF}{MTBF + MTTR + MSRT + MOADT + MAdmDT}. \tag{2.6}$$

Equation 2.6 is more useful in terms of collecting measurable data and updating the value for $A_o$. As seen in Equations 2.4 and 2.6, $A_o$ can be defined in different ways. Specificity and measurability are the factors for why $A_o$ is defined in a more complex format. Consider 2.5 and MLDT's constituent components. It is useful to know if MLDT is increasing or decreasing over a period of time for a system. However, it is more useful to diagnose logistics problems by understanding what component (MSRT, MOADT, MAdmDT) is changing to efficiently determine the cause.

Operational availability includes all logistical down-time in addition to downtime associated with corrective and preventative maintenance. $A_o$ is more conservative than achieved availability or inherent availability. Table 2.2 gives a summary of how each type of availability is defined in terms of uptime and downtime.

Table 2.2. Availability Time Breakdown

| **Availability** | $T_{up}$ | $T_{down}$ |
|---|---|---|
| inherent availability ($A_i$) | MTBF | MTTR |
| achieved availability ($A_a$) | MTBM | $\bar{M}$ |
| operational availability ($A_o$) | MTBF | MTTR+MLDT |
| operational availability ($A_o$) | MTBF | MTTR+MSRT+MOADT+MADMT |

From the Table 2.2, it follows that $A_i \geq A_a \geq A_o$. That is, **operational availability** ($A_o$) is the most conservative definition for system availability in current literature.

The DON's *Operational Availability Handbook* describes $A_o$ as "a key component to the DOD's ability to prevail in battle by ensuring readiness" [8]. This document has not been updated since 2003 and remains the primary instruction for the Navy for assessing system performance. Operational availability is the primary measure for assessing systems throughout their life cycle.

**Operational Availability for a system of systems (SoS)**

It is often the case that a system operated by the DON is performing a critical function which is a result of multiple systems working together. A critical function is a primary capability of the system. A system producing new capabilities as a result of different systems working together is a SoS, implying that many DON SOIs are also SoSs. The International Council on Systems Engineering (INCOSE) defines SoS as a "SOI whose elements are managerially and/or operationally independent systems. These interoperating and/or integrated collections of constituent systems usually produce results unachievable by the individual systems alone." [4, p. 8].

Recall that availability is the probability that a system will function when needed. A complexity problem for calculating $A_o$ arises. A simple solution is to calculate the individual mission operational availability ($A_{o_i}$) for each mission. To calculate the $A_{o_i}$, each component associated with the mission of interest must be determined while disregarding all other components and Equation 2.4 would become Equation 2.7 [9]:

$$A_{o_i} = \frac{MTBF_i}{MTBF_i + MTTR_i + MLDT_i}. \tag{2.7}$$

The alternative solution to calculating $A_{o_i}$ is to calculate the System of Systems operational availability ($A_{o_{SoS}}$). Calculating $A_{o_{SoS}}$ directly is arduous and subject to current research, and is further discussed in Section 2.1.6.

**Inconsistencies with Defining Operational Availability**

It is worth mentioning the inconsistencies associated with using $A_o$. The author has found three main discrepancies with DOD entities utilizing $A_o$:

1. How $A_o$ is defined
2. Different representations of the same equation
3. Incorrect citation of source documents

An explicit definition of $A_o$ must be given along with its calculations. Additionally, the source documentation should always be cited when $A_o$ is used. Different entities define availability in slightly different ways which leads to a variation in how uptime and downtime are counted. Each discrepancy is briefly explained below.

**How $A_o$ is Defined**

Operational availability ($A_o$) is deceptively complex to understand. The term represents a simple relationship that calculates the ratio of time a SOI has been available for use. However, SOI stakeholders interpret the definition of $A_o$ in different ways. It follows that stakeholders must communicate how a system's $A_o$ is calculated. Factors that have the potential to confuse the use of $A_o$ are listed here.

Downtime is counted in different ways. When the equation for $A_o$ is expanded in Equation

2.6, there are five terms that must be determined. SOI stakeholders track measures of performance differently for systems and it follows that delays may be recorded differently. Table 2.3 lists various definitions for $A_o$ that have been found during research.

Table 2.3. Different Definitions for Operational Availability

| **Source and Citation** | $A_o$ **Definition** |
|---|---|
| *Operational Availability Handbook* [8] | $A_o = \frac{MTBF}{MTBF+MTTR+MSRT+MOADT+MAdmDT}$ |
| Blanchard and Fabrycky [2, pp. 492-493] | $A_o = \frac{MTBF}{MTBF+MDT}$ |
| NSWC CIWS Assessment [10, p. 25] | $A_o = \frac{MTBF}{MTBF+MTTR+MLDT+MOADT+MAdmDT}$ |

It is important to note that some definitions in Table 2.3 differ from Blanchard and Fabrycky and the *Operational Availability Handbook*, but are not incorrect. The definitions given by the CIWS reliability, maintainability, and availability (RMA) book and the NSWC CIWS assessment include MLDT in the denominator with MOADT and MAdmDT. This appears to be contradictory to Equation 2.5, but this is a difference in how each source categorizes downtime. NSWC and PEOs count MLDT separately from MOADT and MAdmDT. The *Operational Availability Handbook* categorizes MOADT and MAdmDT as subsets of MLDT. This finding emphasizes the importance of ensuring that the same definition for $A_o$ is understood by all stakeholders.

**Incorrect Citation of Source Documents**

There are several competing source documents that the DON uses to define $A_o$. The Navy's *Operational Availability Handbook* [8] is the most up to date publication on $A_o$. The *Operational Availability Handbook* is maintained by the Assistant Secretary of the Navy and is not to be confused with the Office of Chief of Naval Operations Instruction (OPNAVINST) 3000.12A Operational Availability of Equipment and Weapon Systems [11]. The Navy's *Operational Availability Handbook* replaced OPNAVINST 3000.12A as the standard publication for system performance metrics. DON offices claim both documents as governing publications. One reason for this misunderstanding is that OPNAVINST 3000.12A is easily found on internet search engines using keywords such as availability and DOD while the *Operational Availability Handbook* is not.

### 2.1.4 Reliability

This section briefly reviews reliability theory and how it relates to availability. For a more detailed review of reliability, refer to [2, Ch. 2].

A system contains a collection of components with a failure rate. The failure rate of a system is defined as $\lambda_{system}$. Failure rate can be assumed constant such that the mean time between failure (MTBF) is related to $\lambda_{system}$ by

$$MTBF = \frac{1}{\lambda_{system}}. \tag{2.8}$$

The assumption of a constant failure rate is reserved for parts and systems which exhibit consistent performance characteristics. Additionally, it is not necessary to assume a constant failure rate to determine the reliability of a system. However, if a constant failure rate is assumed, then it allows for the calculation of MTBF.

Assume that the system reliability follows an exponential distribution and is related to $\lambda_{system}$ by

$$R(t) = e^{-\lambda t}. \tag{2.9}$$

For a system of components with associated reliabilities $R_1, R_2, R_3, ..., R_n$ *connected in series*, the overall system reliability is the product of the constituent component reliabilities given by

$$R_{sys_{series}} = \prod_{i=1}^{n} R_i. \tag{2.10}$$

For a system of components with associated reliabilities $R_1, R_2, R_3, ..., R_n$ *connected in parallel*, the overall system reliability is the product of the constituent component reliabilities given by

$$R_{sys_{parallel}} = 1 - \prod_{i=1}^{n}(1 - R_i). \tag{2.11}$$

For a combination of components in series and parallel, the overall reliability of the system can be obtained by using the combination of equations for series and parallel component reliabilities, given by Equations 2.10 and 2.11.

### 2.1.5 The Stakeholders of Operational Availability

This subsection describes the stakeholders of system performance metrics and how they interact with each other. The primary stakeholders for system performance metrics in the context of this thesis are the following:

- Naval Surface Warfare Center (NSWC) Corona
- The Fleet
- Program Executive Offices (PEO)s

Each stakeholder is briefly described, followed by a functional diagram illustrating stakeholder interactions.

**Program Executive Office (PEO)**

Program Executive Office (PEO)s are a subset of Naval Sea Systems Command (NAVSEA). Within the DON, there are six PEO branches. Each PEO is responsible for the life-cycle management of the programs under their responsibility [12]. It is emphasized that life-cycle management implies all phases of the JCIDS process. PEO offices are responsible for the design, construction, delivery, support, and disposal of the system. PEO offices are physically located at the Washington Navy Yard in Washington, D.C. The following office branches make up the U.S. Navy (USN) PEO branches with their associated program responsibilities [12]:

- ***PEO Aircraft Carriers:*** Responsible for the life-cycle management of aircraft carriers and interfacing systems with aircraft carriers.
- ***PEO Columbia:*** Responsible for the design and delivery of the ballistic missile submarine replacement of the Ohio Class submarine. This office formerly under PEO

Submarines and has become a separate branch.

- ***PEO Integrated Integrated Warfare Systems (IWS):*** Responsible for combat systems within the navy. An example of a program under PEO IWS is the CIWS program.
- ***PEO Ships:*** Responsible for non-nuclear-powered ships within the DON.
- ***PEO Submarines:*** Responsible for U.S. Navy submarines in addition to "advanced undersea and anti-submarine systems" [12].
- ***PEO Unmanned and Small Combatants:*** Responsible for unmanned sea-going systems, mine warfare, and small surface combatant craft.

**The Fleet**

The fleet is the sailors and personnel tasked with operating combat systems for the DON. Recall Figure 2.3. At a high level, the fleet outputs raw data pertaining to systems. This data is sent to multiple different stakeholders. The majority of data output from ships is maintenance related. This data is sent to NSWC Corona to be verified and validated prior to analysis. The fleet is also the primary receiver of simplified lessons-learned reports from the cognizant PEO branches.

**Naval Surface Warfare Center (NSWC) Corona**

Naval Surface Warfare Center (NSWC) Corona is a subset of Naval Sea Systems Command (NAVSEA), located in Corona, CA. Figure 2.2 is an organization chart of the NAVSEA command structure, illustrating the relationships between different stakeholders within NAVSEA.

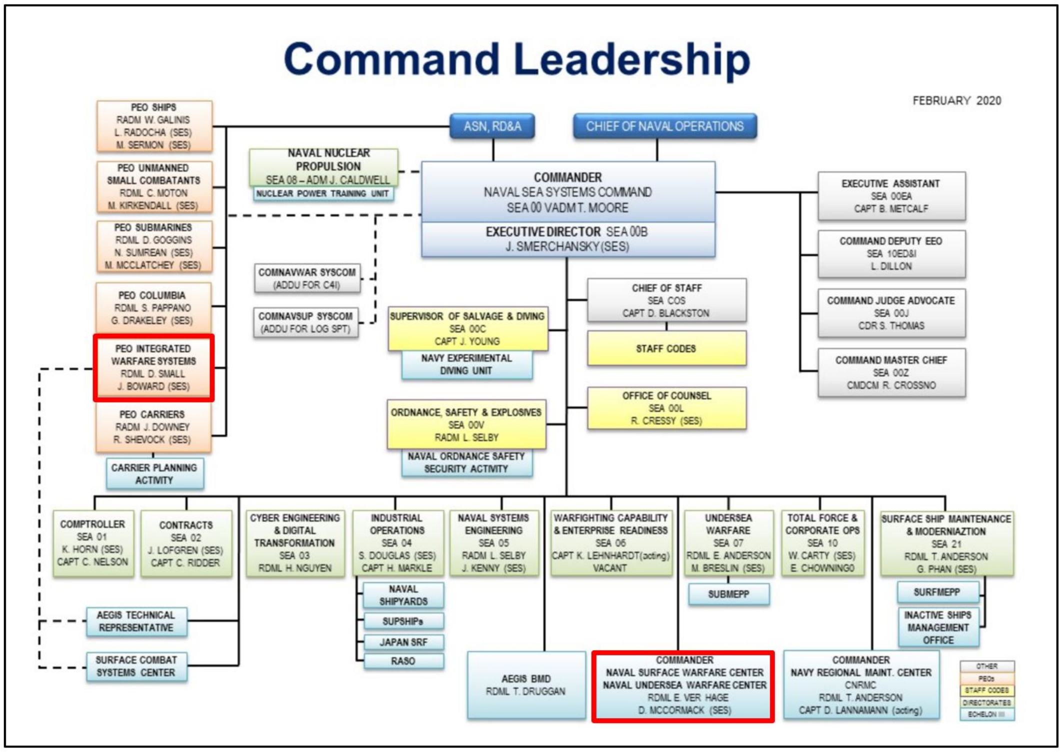


Figure 2.2. NAVSEA Organization Chart
Adapted from [13].

The NSWC Corona is the DON's only independent analysis and assessment center [14]. NSWC Corona is independent because they are not responsible for the life-cycle management of the systems they monitor and they do not answer directly to any PEO. Additionally, it can be seen in Figure 2.2 that NSWC Corona reports to the NSWC command, which reports directly to the commander of NAVSEA. PEOs have no bearing on how NSWC Corona conducts analysis.

NSWC Corona has approximately 3,200 personnel under its employment and is a combination of civilian engineers, scientists, sailors, and contractors. The primary capabilities of NSWC Corona are the following:

1. Assess system performance and readiness
2. Provide independent analysis
3. Use relevant data on systems

A primary function of NSWC Corona is to conduct and provide independent assessments of weapon systems to impactful stakeholders. Generally, NSWC provides SOI analysis reports to the cognizant PEO in the effort to make more informed decisions. The main repository of system performance data is stored and calculated in a collection of servers called the MRDB.

**Material Readiness Database (MRDB)**

The Chief of Naval Operations (CNO) chartered the MRDB in 1988. The MRDB is the leading readiness database for all shipboard systems. The database infrastructure is managed by NAVSEA 21 (refer to Figure 2.2 for organization chart). The MRDB is a collection of servers within NSWC Corona that store data and update performance metric calculations for tracked systems.

The MRDB updates performance metrics using external data obtained from the fleet. Data sources that input into the MRDB include the following:

- Naval Sea Logistics Center (NSLC) Ship Maintenance Material Management (3M)
- Surface Maintenance Engineering Planning Program (SURFMEPP) Ship Data
- electronic departure from specification (eDFS)
- Shipboard Automated Management Maintenance Systems (SAMMS)
- maintenance figure of merit (MFOM) Casualty Report (CASREP)
- OP-30S/OP-05A sheets
- Marine Gas Turbine Information System (MGTIS)
- Navy Maintenance Database-Platform (NMD-R)
- Web-Based Scheduling (WebSked)
- Total Ship Readiness Assessment (TSRA)
- electronic log application (eLog)
- Navy Data Environment (NDE)
- naval vessel register (NVR)
- Inspection and Survey (INSURV)
- Configuration Data Managers Database-Open Architecture (CDMD-OA)
- Tech Assist, Assessments and Scheduling Information (TAAS-INFO)
- Information Technology Service Management (ITSM)-Remedy
- Commander, Naval Surface Forces Pacific (CNSP)

- Type Commander (TYCOM)
- Commander, Navy Regional Maintenance (CNRM)
- NAVSEA-21 Spreadsheets
- Technical Assistance Visit Report (TAVR)
- Sub Builders

For a comprehensive list of data sources, refer to [15, pp. 39-41]. The data is sent to NSWC Corona and is verified and validated by the system of interest (SOI) Validation group. The group checks the data for logical errors and completeness. If there is a question on data entries, NSWC Corona has the capability in some situations to resolve potential errors, but not all situations. There are a large number of possible causes that result in performance data errors and NSWC does not have the ability to remedy all possibilities [16]. The data is then uploaded to a collection of servers where running calculations update performance metrics. Calculations for reliability and availability of the system are based around the accepted system reliability block diagram (RBD). For each system tracked by the MRDB, a RBD is programmed and approved between the SOI Validation Group at NSWC Corona and the system's program manager.

As performance metric calculations are updated, the results become available for review on the MRDB web application. Within the MRDB web application, there are many different ways to view results. In general, a SOI is first selected. Then, performance metric results can be arranged by home port, geographic location, hull number, or world wide. Table 2.4 gives a break down of the type of SOIs that are currently tracked by the MRDB.

Table 2.4. Systems Tracked by MRDB by System Classification. Source: [17].

| System Type | Total Tracked by MRDB |
|---|---|
| Combat Systems | 123 |
| HM&E | 107 |
| C4I | 128 |
| System of Systems | 13 |
| **Total** | **371** |

Table 2.4 shows that there is a significant number of systems tracked by the MRDB. Combat systems generally refers to weapon systems or systems that have a direct effect on the performance of a weapon system. An example of a non-weapon system that is still classified as a combat system is the AN/SPY-6 Air and Missile Defense family of radars. Hull, mechanical, or electrical (HME) systems are any system that are falls within the description. Refrigeration systems or propulsion shaft systems would be examples of HME systems. An example system that is classified as a command, control, communications, computers, and intelligence (C4I) system is ultra high frequency (UHF) satellite communications (SATCOM). The SoSs tracked by the MRDB are those systems that are comprised of a collection of other systems to accomplish a specific function.

It is important to note that Table 2.4 counts system variants as different systems. For example, the Phalanx CIWS Block 1B and 1A variants are different systems and both are tracked by the MRDB. So, even though Table 2.4 shows that over 370 systems are tracked, this total includes variants within the same system family. Variants of the same system must be treated as separate systems because of the difference in parts requirements and variations in the systems' RBDs.

At the program level, system assessments normally include results of every system pooled together.

Using the updated performance metrics, NSWC Corona provides several different kinds of assessments to PEOs to make informed decisions on the life-cycle management of the system. These assessments are shown in Figure 2.3.

The MRDB conducts performance assessments on its own calculations using commercial off-the-shelf (COTS) software such as ReliaSoft. During a discussion with the Chief Engineer of the MRDB, he reported that COTS software agreed with calculation outputs from MRDB. The MRDB uses its own collection of in-house servers to update performance calculations because it is interfaced with incoming data from the fleet. Whenever a COTS software is used to compare results, a static data file is required. Additional information regarding how the MRDB performs calculations is located in Section 2.1.6.

**Stakeholder Interactions and Flow Diagram**

Figure 2.3 is a high-level functional flow block diagram for the MRDB and performance metrics in the DON. The dark arrows give the primary flow of information throughout the process while red arrows are tertiary relationships with other entities. For example, Figure 2.3 shows that the SOI Validation Group interacts with the PEO to develop and approve an RBD for use in performance metric calculations. This process is not routine and is done as changes to the system are made. Because the MRDB uses RBDs to update performance metrics, the process is slow to add new systems. However, MRDB still tracks most critical systems in the DON.

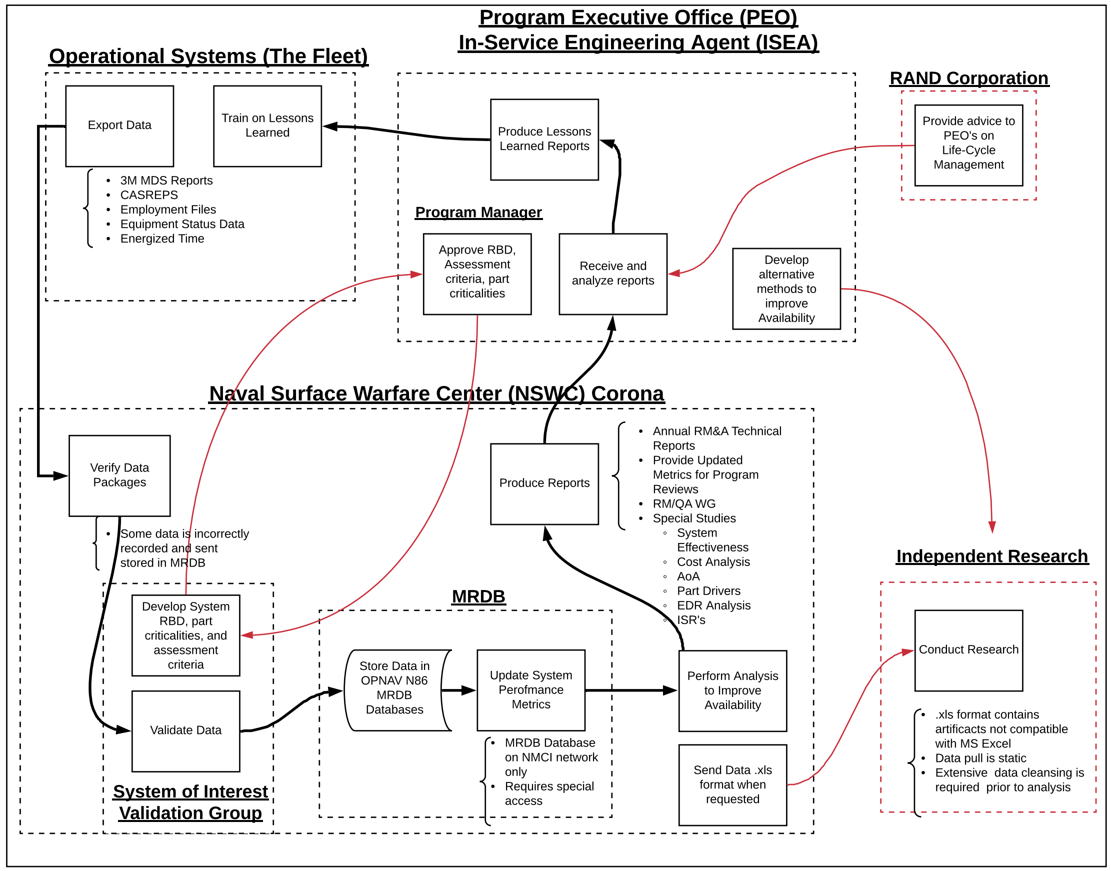


Figure 2.3. Detailed Functional Block Diagram for the MRDB
Adapted from [10, p. 5].

### 2.1.6 How MRDB Performs Calculations

Initially, the author expected that the way the MRDB calculates $A_o$ would be similar to Equation 2.6. In reality, calculating the availability of a system by directly determining the terms in Equation 2.6 is not practical. This subsection describes how the MRDB calculates $A_o$ for systems.

The MRDB's method for determining $A_o$ is centered around the SOI RBD. If a system performs multiple primary missions, then individual RBDs are written and approved for the SOI and the availability for individual missions and combined missions are calculated. Figure 2.4 gives a general overview of the MRDB method of calculating $A_o$.

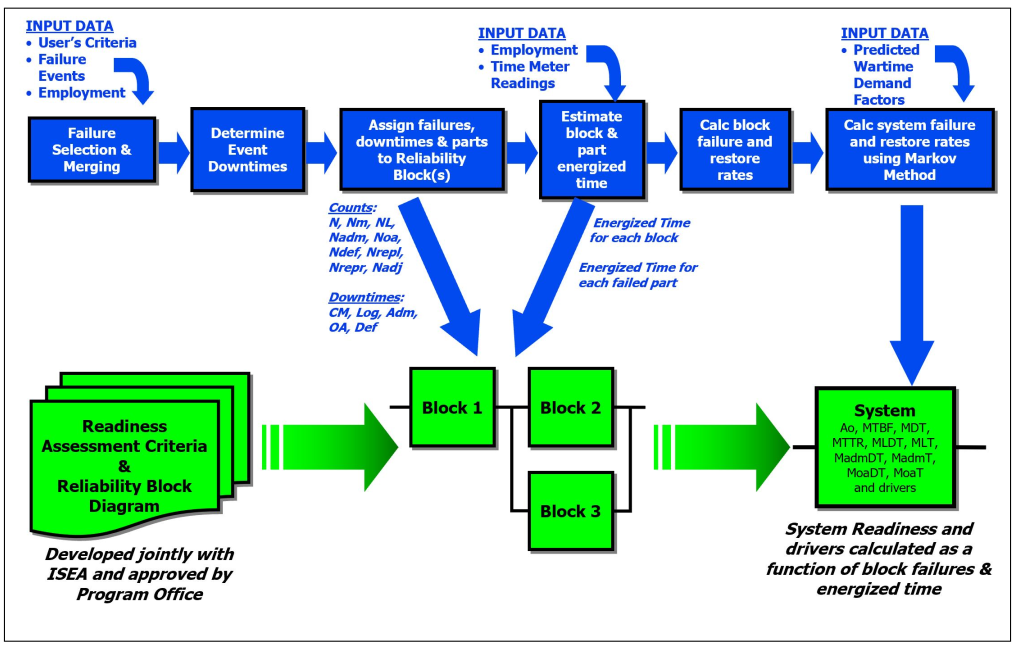


Figure 2.4. MRDB $A_o$ Calculation Process. Source: [18].

Figure 2.4 shows the general process of how calculations are performed for SOIs tracked by the MRDB. The first general step is to determine how downtime is counted.

#### Failure Selection and Event Downtimes

Figure 2.5 shows an generic example of a corrective maintenance timeline for a SOI.

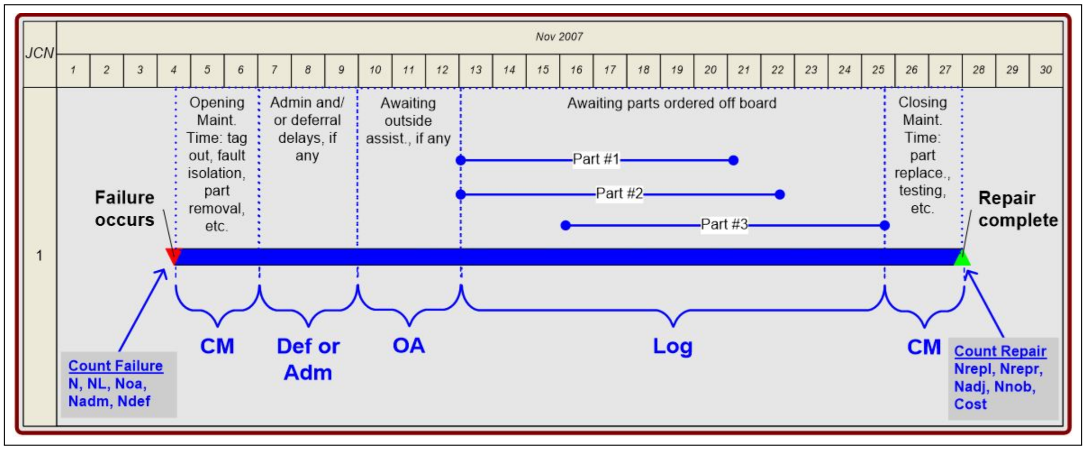


Figure 2.5. MRDB Downtime Count Diagram. Source: [18].

The downtime counter begins when a failure occurs. Downtime is then divided into several different classifications. The following list of times with subscripts directly corresponds to the subscripts shown in Figure 2.5:

- $T_{CM}$: Corrective Maintenance Time: The time elapsed to complete corrective maintenance actions. This time starts when a Job Control Number (JCN) is assigned to the maintenance action. In general, a JCN is a unique serial number logged in the ship's maintenance logs that indicate the requirement to perform maintenance (both corrective and preventative).
- $T_{Def}$ or $T_{ADM}$: Deferral and Administrative delays: Downtime related to lag time in required administrative actions or intentionally deferring maintenance.
- $T_{OA}$: Outside Technical Assistance: In some cases the corrective maintenance for a SOI cannot be completed by the crew. The common term in the USN is that the maintenance action is "beyond the capability of ship's force" or "outside of ship's force capability." $T_{OA}$ is the downtime associated with outside technical assistance traveling to the SOI.
- $T_{Log}$: Logistic downtime: $T_{Log}$ counts the downtime associated with a SOI waiting for parts to arrive.

There are situations where multiple maintenance actions must be performed on the same subsystem. This implies that there are overlapping JCNs that are contributing to the same downtime of the affected SOI. To avoid counting multiple downtimes, the MRDB merges the downtime of JCNs that affect the same SOI. This is graphically represented by Figure 2.6.

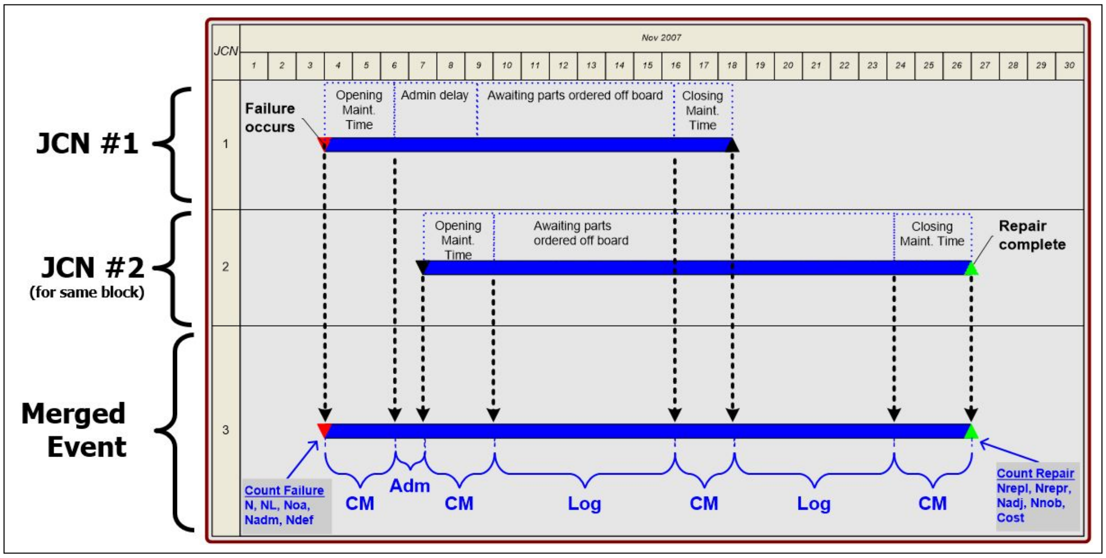


Figure 2.6. MRDB Downtime Count Diagram with Overlapping Events. Source: [18].

Figure 2.6 shows that the overlapping timelines of the different JCNs are merged to correctly reflect the actual downtime of the system.

**KPPs Subsystem Block Calculations**

Downtime is counted, merged, and attributed to subsystem blocks. As the various downtime types are assigned, Block-KPPs and part-KPPs are updated. Table 2.5 gives a summary of all the subsystem block and part performance metrics that are calculated and available for view.

Table 2.5. Number of Systems Tracked by the MRDB. Source: [18].

| **Part Metrics** | |
|---|---|
| **Part Metric Name** | **Part Metric Equation** |
| mean time between failure (MTBF) | $MTBF_{part} = \frac{T_{e_{part}}}{N_{part}}$ |
| mean down time (MDT) | $MDT_{part} = \frac{T_{d_{part}}}{N_{repair_{part}}+N_{replace_{part}}+N_{adjust_{part}}}$ |
| mean time to repair (MTTR) | $MTTR_{part} = \frac{T_{cm_{part}}}{N_{repair_{part}}+N_{replace_{part}}+N_{adjust_{part}}}$ |
| mean logistics delay time (MLDT) | $MLDT_{part} = \frac{Tlog_{part}}{N_{replace_{part}}}$ |
| mean logistics time (MLT) | $MLT_{part} = \frac{Tlog_{part}}{NL_{part}}$ |
| Not on-Board (NoB) | $NoB_{part} = \frac{NL_{part}}{N_{replace_{part}}}$ |
| **Block Metrics** | |
| **Block Metric Name** | **Block Metric Equation** |
| operational availability ($A_o$) | $A_{o_{block}} = \frac{MTBF_{block}}{MTBF_{block}+MDT_{block}}$ |
| mean time between failure (MTBF) | $MTBF_{block} = \frac{Te_{block}}{N_{block}}$ |
| mean time between failure (MTBF) with Demand Factor (DF) | $MTBF_{block} = \frac{Te_{block}}{N_{block}*DF_{block}}$ |
| mean down time (MDT) | $MDT_{block} = \frac{Td_{block}}{Nm_{block}}$ |
| mean time to repair (MTTR) | $MTTR_{block} = \frac{Tcm_{block}}{Nm_{block}}$ |
| mean logistics delay time (MLDT) | $MLDT_{block} = \frac{Tlog_{block}}{Nm_{block}}$ |
| mean logistics time (MLT) | $MLT_{block} = \frac{Tlog_{Tlog_{block}}}{NL_{block}}$ |
| mean administrative delay time (MAdmDT) | $MAdmDT_{block} = \frac{Tadm_{block}}{Nm_{block}}$ |
| mean administrative time (MAdmT) | $MAdmT_{block} = \frac{Tadm_{block}}{Nadm_{block}}$ |
| mean outside assist delay time (MOADT) | $MOADT_{block} = \frac{Toa_{block}}{Nm_{block}}$ |
| mean outside assist time (MOAT) | $MOAT_{block} = \frac{Toa_{block}}{Noa_{block}}$ |

It is important to note that subsystem block metrics and part metrics are calculated using equations that produce closed form solutions shown in Table 2.5. System level metrics cannot be calculated using the same techniques for several reasons. The first complication is **redundancy**. Systems are often designed with redundancy so that the loss of a subsystem will not cause a complete system failure. Additionally, complex subsystem block interdependencies make it difficult to determine when a system is available to execute a mission.

That is to say, there exists more than one configuration of working and failed subsystems where a SOI can function. These complexities require either simulation/modeling or Markov processes to estimate $A_o$.

**System Metric Calculations**

Performance metric calculations at the system level are more complicated to calculate than subsystem or parts level calculations. Subsystem and parts level calculations are simple because each part and subsystem can be in only one of two states: up and down. At the system level, redundancy in operation can make it difficult to calculate how a part failure leads to a system level failure. There are many combinations of states that a system can take while still being available to execute a primary mission. This added complexity at the system level requires higher level modeling to calculate system $A_o$ [19].

One of the analysis techniques that can be used to calculate $A_o$ at the system level is a Markov model. A Markov model is a stochastic process that describes the process of a system in terms of the possible states the system can be in and the probabilities of moving from one state to another. The MRDB calculates system level $A_o$ using Markov models [18]. The general form of the Markov model for $A_o$ is given by Equation 2.12 as

$$A_o = \frac{1}{1 + \sum_{i=1}^{n} \frac{\lambda_i}{\mu_i}}, \tag{2.12}$$

where $\lambda_i$ is the failure rate of subsystem $i$ and $\mu_i$ is the restore rate of subsystem $i$.

The MRDB uses specific language in defining how MRDB calculates availability. The following definitions are used to form the method the MRDB uses to calculate $A_o$ [18]:

- $N_i$ := Number of failure events for the $ith$ block.
- $N_{m_i}$ := Number of failure events with measured downtime for block $i$.
- $D_i$ := Total downtime resulting from $N_{m_i}$ failure events for block $i$.
- $T_{m_i}$ := Total energized/stress time for block $i$.
- $D_{f_i}$ := Demand Factor for block $i$. The relevant PEO approves the demand factor for each block in the system. The demand factor is based on a 120-day wartime mission usage. An alternate definition for $D_{f_i}$ is the probability that block $i$ will be required

during a nominal 120-day wartime mission.

Suppose there is a system which has a RBD consisting of $n$ blocks. Then, the RBD can be represented as a series of blocks and would look something like Figure 2.7.

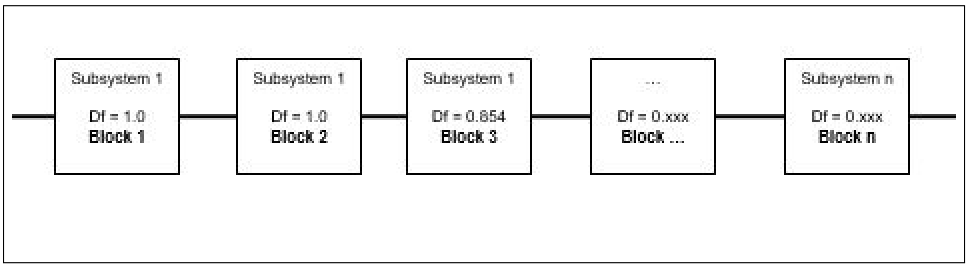


Figure 2.7. Sample reliability block diagram (RBD)

Each block in Figure 2.7 is a subsystem represented by a failure rate ($\lambda_i$), a restore rate ($\mu_i$), and a demand factor ($D_{f_i}$). The failure rate and restore rate for each subsystem block is calculated using Equations 2.13 and 2.14.

$$\lambda_i = \frac{N_i}{T_{m_i}} D f_i \tag{2.13}$$

$$\mu_i = \frac{N m_i}{D_i} \tag{2.14}$$

Equations 2.13 and 2.14 are substituted into equation 2.15 to get

$$A_o = \frac{1}{1 + \sum_{i=1}^{n} \frac{\lambda_i}{\mu_i}} = \frac{1}{1 + \sum_{i=1}^{n} \frac{N_i D_i}{N_{m_i} T_{m_i}} D_{f_i}}. \tag{2.15}$$

It is important to note the effect of the demand factor on Equation 2.15. As the limit of the demand factor goes to zero, Equation 2.15 approaches one or 100% availability. This result makes sense since a block with low demand factor implies that it is unlikely to be needed in a wartime environment. Therefore, the block failing should not be counted as much towards the overall $A_o$. It is also important to note that, for each primary mission of a SOI, a unique

RBD is required. This is because Markov models depend on defining the states of the system. As an example, the CIWS platform does not need an electro-optical subsystem to perform the Anti-Air Warfare (AAW) mission. So it follows that the electro-optical subsystem block would not be included in the AAW specific RBD.

## 2.2 Current Research

There is a multitude of efforts towards improving the life-cycle management of systems by utilizing data and performance metrics. These efforts primarily try to either increase system performance or attempt to explain why system performance is lacking. Research can be organized into three general areas:

1. Address Systemic Problems
2. Numerical Techniques to Improve $A_o$
3. Consider performance metrics other than $A_o$

This section explains the different areas focused on increasing system readiness by discussing the general areas stated above. Furthermore, this section explains how this research fits within, and differs from, the context of current research.

### 2.2.1 Address Systemic Problems

The first general area of research is to point out systemic problems associated with life-cycle management. The RAND Corporation is a non-profit think tank that conducts studies on a wide variety of disciplines. Recently, NAVSEA and PEOs sponsored a RAND study titled "An Approach to Life-Cycle Management of Shipboard Equipment" [15]. In the report, researchers documented underlying problems associated with calculating readiness for DON systems. The most apparent problem they documented was the Navy's lack of centralized data or a common data standard [15, pp. 54-55]. As illustrated in Section 2.1.5, the MRDB has to verify and validate data from many different databases to build a performance picture for a system with coherent performance metrics. When NSWC Corona says that they provide the functions of data verification and validation, it means data consolidation. Data sent to NSWC Corona can arrive in paper format, removable media, or accessed through web applications. The interface between individual data exports and NSWC Corona is different. The fact that NSWC Corona performs this enormously complex function means that the

MRDB is quite possibly the only collection of servers within the DON that attempts to maintain consolidated maintenance and performance data on systems.

The RAND study goes on to cite data accuracy issues. Much of the data used to update performance metrics for systems comes from the 3M program. The 3M manual is the governing document for preventative and corrective maintenance for systems in the 3M program [20]. For maintenance conducted on ships, it is generally true that it is the responsibility of the command's 3M coordinator to ensure the accuracy of maintenance records. However, humans fill out required forms under the 3M program and errors occur to varying degrees. From the author's personal experience, 3M inspections of ships can reveal mismanaged records with alarmingly incomplete information on maintenance information. RAND agreed with the author's personal experience [15, pp. 54-55]. The MRDB and NSWC Corona can have the most robust technological infrastructure, engineers, and calculations, but erroneous input data results in erroneous availability calculations. The RAND report was correct in claiming that the systemic problem of data management is within the control of the DON to solve.

The RAND study does an excellent job of exploring the stakeholders associated with life-cycle management within the Navy and pointing out major systemic problems with data management, command structures, and common practices. The RAND report inadequately provides recommendations to the DON with pieces of general advice. Changes such as force restructuring, data server migrations, maintenance program overhauls take significant amounts of time and money. [15] inadequately addresses the complexity and cost of the recommendations the report suggests making. Additionally, the DOD was already well aware of data management problems before this report was released. In an effort to begin solving the DON's data problem, the DON released its "Strategy for Data and Analytics Optimization" in September of 2017 [21].

Over the last two decades, federal agencies and researchers have critiqued systematic problems within DOD acquisitions. In 2003, the Office of the Secretary of Defense [22] critiqued similar problems mentioned in [15]. The work of [22] identifies key systematic problems within DOD acquisitions such as programs having poorly defined RMA requirements or having unachievable reliability requirements. In January of 2020, the Government Accountability Office (GAO) released an audit [23] reviewing seven major DOD weapon system programs on their RMA practices. The report found that five of the seven programs failed to address suggested practices that were mentioned in 2003 by [22]. It would seem that major weapon systems programs are not improving system $A_o$ by critiquing systematic problems.

Wahid et al. [24] takes a different approach to addressing systematic problems by identifying downtime influence factors. Recall Figure 2.1, which introduces the ways in which uptime and downtime can be classified. This research takes this approach and attempts to categorize the top 50 downtime influence factors for systems associated with warships. Using the the list of downtime influence factors, [24] presents a method for improving system $A_o$ by ranking and addressing the most important downtime influence factors first. This is a novel approach to increasing availability because [24] attempts to increase the granularity for why downtime occurred. This aids program managers in creating solutions because the source of the downtime is more specifically defined than vague classifications like MLDT. What [24] does not provide is a method for improving $A_o$ that can easily be applied to pre-existing system performance data. The research presents much needed context to the operational warship environment and sources of downtime. But this context is recommended to be used in generalized steps that are not easily applied to system performance data. Separate research is required to define under what conditions the guidance in [24] is valid.

**Performance Metrics vs. KPPs**

It is important to note the use of language between **performance metrics** and KPPs. A performance metric is a generic term to describe a calculation for assessing one or more performance aspects of a SOI. A performance metric is simply an indicator for SOI performance. A KPP is a term defined by the Defense Acquisition Guide (DAG). A KPP is a performance metric that must attain a required value in order for the system to perform up to its written specifications [25]. In general system $A_o$ calculations should not be called KPPs unless they meet the definition given in the DAG. When a KPP is below its required value, this should signal to stakeholders that a change in system design or support structure should occur so that the system performs as designed. Most system $A_o$ calculations are not accompanied by threshold and objective values. Therefore, $A_o$ calculations should be considered simply performance metrics. “Performance metrics” is a term used throughout this thesis to specify that those metrics do not carry objective and threshold requirements with them.

### 2.2.2 Numerical Techniques to Improve $A_o$

One problem associated with calculating $A_o$ for Navy systems is that, often, they perform multiple primary missions. For example, the Phalanx CIWS aids surface ships in AAW and Anti-Surface Warfare (ASuW). In this example, the PEO has the ability to report three availability metrics:

- $A_{O_{AAW}}$
- $A_{O_{ASuW}}$
- $A_{O_{Combined}}$

It becomes difficult to determine which availability matters and what portions of the system should be focused on as a result of changing availabilities. Some subsystem blocks can affect both primary missions while other subsystem blocks only affect one mission or none at all. Each primary mission requires a unique set of subsystem blocks that are represented by a RBD. It follows that all three availabilities are individually calculated based on their respective RBD.

To account for added complexities in systems, research has moved towards higher-level analysis techniques to account for the many variations in possible system states. Markov models are one example that have been previously explained in Section 2.1.6. Another higher-level analysis technique is the use of Monte-Carlo simulations. Markov models and Monte-Carlo simulations are methods of estimating the availability for a system. As a result, any forecasting techniques or optimization techniques require similar probability models to function correctly. This fact makes low-level optimization calculations very difficult to accomplish.

Researchers at Sandia National Laboratories [9] provide an overview of the complexities in calculating the $A_o$ for SoSs. The research explains that dependencies that exist within complex systems make it necessary to perform higher-level modeling to calculate $A_o$. The research in [9] goes on to apply the commercial software SoSAT. In a similar vein, Sols [26] argues that a method for determining performance for SoSs is needed as major systems become more interconnected and complex. Unfortunately, none of the suggestions given in these sources can be implemented with low-level calculations and simple methodologies. These sources clearly show that calculating $A_o$ at the SoS level requires modeling software and a high level of mathematical skills.

### 2.2.3 Consider KPPs other than $A_o$

Several academic research projects have critiqued the inadequacies of $A_o$. These efforts critique $A_o$ as a useful KPP and/or propose shifting focus to different metrics as KPPs.

**The Importance of MLDT**

NPS's Apte Aruna and Rene Rendon previously conducted research in conjunction with PEO IWS and NSWC Corona, focusing on the Phalanx CIWS system [27], [28]. The works of Aruna and Rendon explain how KPPs are misused within the DON. Aruna and Rendon [28] show that MLDT can be the most important downtime factor for improving system $A_o$ under certain conditions. Recall Equation 2.4 for $A_o$:

$$A_o = \frac{MTBF}{MTBF + MTTR + MLDT}. \tag{2.4}$$

The work of [28] shows that, under typical Navy system $A_o$ conditions, MLDT has higher elasticity than MTBF or MTTR with respect to $A_o$. These system conditions include the following criteria:

1. System $A_o$ is normally above 0.50 or 50%.
2. $MTBF > MTTR + MLDT$
3. $MLDT > MTTR$

Consider Equation 2.4 a function such that $A_o$ is a function of input variables MTBF, MTTR, and MLDT. Elasticity, in the use of mathematical functions, is a measure of relative percentage change of the function output compared to the relative change of the function input [29]. Aruna and Rendon [28] correctly show that MLDT has more elasticity with $A_o$ compared to MTBF and MTTR. Since MLDT has more elasticity than the other two input variables for the function $A_o$, then it follows that $A_o$ has a higher potential to change based on a change in MLDT. This suggests that plans to improve system $A_o$ should involve minimizing MLDT. It follows that if system performance data satisfy the criteria given in [28], then improving MLDT has a greater impact on increasing system $A_o$ compared to any other downtime factor.

Aruna [27] further investigates the driving factors of MLDT by determining the dominant constituent of logistics downtime. Recall that $MLDT = MSRT + MOADT + MAdmDT$. Aruna [27] hypothesize that mean administrative delay time (MAdmDT) is an insignificant contribution to MLDT, suggesting that the primary drivers are MSRT and MOADT. Where [27] falls short is synthesizing methods to investigate why MLDT for a SOI may be unacceptably high.

A spectrum exists on which different analytical techniques to improve $A_o$ can be placed. On one extreme are high-complexity techniques such as Markov models, Monte Carlo simulations, and well developed commercial simulation software. On the other end of the spectrum are low-complexity techniques that utilize simple performance metrics that are direct measurements of system performance and can be implemented immediately. Not enough research has been done to exploit low-level performance metric calculations that can apply towards minimizing downtime factors. The trade-off in using low-level calculations is that it may be difficult to predict the overall change in system $A_o$.

## 2.3 Chapter Summary

This chapter discussed the necessary background and current research to understand the research conducted in subsequent chapters. In Section 2.1, the broad topics of availability, reliability, and performance metrics were discussed within the context of the DON and the Material Readiness Database (MRDB). Section 2.2 discussed current research associated with improving overall system availability, and the chapter concluded by identifying that there is a gap in research efforts with respect to applying low-level performance metric calculations to DON system performance data.

# CHAPTER 3:
# Issues with Optimizing Operational Availability

Chapter 2 described the background of performance metrics and systems within the DON and NAVSEA in addition to the current research related to improving $A_o$ and supply chain management. As mentioned in Chapter 1, this thesis intended to develop a relatively simple optimization method for increasing $A_o$ by focusing on MLDT reduction. Ultimately, an optimization model is determined to be infeasible. This chapter captures the effort of creating an optimization method for CIWS availability and why Program Managers should not seek this route in analysis assistance. This chapter reviews the original problem statement, the proof(s) of concept (POC) for the research, and the key findings. The next section describes the key findings of this chapter.

## 3.1 Overview

The goal of an optimization model for a system within the context of this thesis is to improve overall $A_o$ by identifying parts to minimize the logistics delay time. A reduction in logistics delay time for selected parts would result in a reduction of the overall MLDT, causing the overall $A_o$ to increase. A secondary goal of the optimization is to provide an $A_o$ cost-benefit analysis so that program managers can make informed decisions related to changes in logistics planning. This section discusses numerous challenges to accomplishing the optimization model.

### 3.1.1 Optimization Model Challenges

The first challenge to building an optimization model is documenting accomplished work. Interviews revealed that a previous $A_o$ optimization modeling project exists which uses Matlab as the chosen software platform [16]. The author made requests for documentation on the optimization model to establish accomplished research. These requests for any available documentation relating to the recent project uncovered no results [30], [31].

The second challenge is that MRDB system data is inaccessible to researchers and difficult to validate. The MRDB web browser used to access system data is located on the Navy and Marine Corps Intranet (NMCI). If a researcher does not have access to NMCI, then it is challenging to access the MRDB's browser remotely. Researchers without NMCI access must request data in MS Excel format without exploring the capabilities of the MRDB web browser. This limitation means that researchers must request data without having a full understanding of how system data is stored and what types of information are available for research. Once the MRDB converts system data to MS Excel, the challenge of validity arises. Review of the data produces the following problems and observations:

- Some number fields within MS Excel are text fields rather than number fields. This exporting error causes calculations to skip those fields. The current solution to this problem is to change data fields back to number format manually, an arduous task for large data sets.
- Ghost markings can appear in front of number sequences. For example, a national item identification number (NIIN) can appear with a "-" before the number sequence. These markings make it very difficult to match the same part numbers together, and there is no solution to this problem.
- Various data fields appear blank for unknown reasons. For example, approximately 7% to 9% of cost data is blank.
- The data export process from the MRDB to MS Excel may experience data loss. Rows of data entries may be lost during a data pull and require the MRDB engineer to check the accuracy of the data export. If a researcher does not have access to the MRDB, then exported data cannot be validated. A full audit of the exported data in .xlsx format against the MRDB results is crucial.

Cost data is the third challenge. The cost of replacement parts varies greatly from FY14 to FY19. Part cost information both increases and decreases, suggesting that multiple external factors affect the cost of replacement parts. The high variance in replacement cost data necessarily implies a high level of uncertainty in any cost-benefit analysis. In some cases, replacement part costs have increased over 1,000% from FY14 to FY19. On one occasion, the cost of a replacement part increased over 10,000% from FY14 to FY19.

Variance in factors contributing to system uptime and downtime is the fourth challenge. For instance, when system data is categorized by homeport, the variance in MTBF is significant enough to heavily impact the $A_o$ result. This observation means that an adjustment to the MLDT of those systems would not necessarily guarantee the $A_o$ to increase. The performance data from fiscal year to fiscal year is inconsistent and requires further analysis of categorical factors.

### 3.1.2 Observations of Current Practices

Several findings on the current practices of reporting system performance are worth nothing. In general, stakeholders view system performance at the fleet level, where every operational system is pooled together for analysis. This practice of grouping systems together is due to the relatively low sample sizes of performance data present at each homeport or operational unit. Very little has been done to explore categorical factors and their importance on $A_o$ and MLDT. There is too much emphasis on $A_o$ to address the question of system readiness. Viewing system performance through $A_o$ alone can be misleading [32]. Methods to improve system performance should include lower-level performance metrics and categorical factors.

### 3.1.3 MRDB Data Export

System performance data was obtained on the Phalanx CIWS Block 1B system from the MRDB to conduct analysis. The data, along with other select materials, are unclassified controlled information, For Official Use Only (FOUO), distribution statement D. As a result of the distribution restriction of the information, specific findings related to the data are referenced in the supplemental case study. More general statements about trends that do not include specific part names or dollar values appear in the main body of this thesis.

## 3.2 Problem Statement and Motivation

The PEO IWS office seeks to improve system performance of the Phalanx CIWS Block 1B system by strategically investing additional funding into the reduction of MLDT. A problem associated with system performance and availability is logistic downtime. Unexpected delays in parts availability, arrival times, maintenance equipment availability and shipping estimates are common occurrences throughout Navy operations.

The PEO IWS for the Navy is interested in improving the system performance of the Phalanx Close-In Weapon System (CIWS) by optimizing MLDT for components associated with

CIWS maintenance. PEO IWS office code 11 has asked the SE Department at NPS for assistance with an optimization model.

The PEO IWS office overseeing the CIWS program coordinates with NSWC Corona and the MRDB to provide data for developing $A_o$ optimization models. CIWS performance data is used to validate POCs. As mentioned in Chapter 2, the relevant PEO receives numerous reports related to their SOIs based on data analyzed by NSWC Corona and the MRDB. The PEOs under NAVSEA are located in the Washington Navy Yard in Washington, D.C., while NSWC Corona is in Corona, CA.

Recall Equation 2.6 where MLDT is expanded into its constituent components:

$$A_o = \frac{MTBF}{MTBF + MTTR + MSRT + MOADT + MAdmDT}. \tag{2.6}$$

The PEO IWS contacted the SE Department at NPS to see if it was possible to develop a cost-effective optimization for the Phalanx Block 1B CIWS system.

### 3.2.1 Initial Feasibility Assessment for Problem Statement

Chapter 2 shows that research exists to support the claim that reducing the overall MLDT of a system affects $A_o$ more compared to MTBF. The PEO IWS office also stated that they have pre-existing MTBF reduction programs intended to improve $A_o$. A MLDT optimization model intends to improve system $A_o$ by a different approach. A multitude of data is also available on these systems tracked by the MRDB. Massive amounts of information are verified, merged, and validated into a consolidated set of databases. At a glance, it appears that the data is available to conduct such an optimization. The initial problem statement of this research seemed to be promising, along with the following conclusions.

- Data exists to build an optimization model.
- The MRDB tracks CIWS performance.
- Research has shown that MLDT reduction can significantly improve $A_o$.
- The PEO IWS office has admitted that they need statistical evidence to justify an investment in MLDT reduction, so a capability gap exists.

Recall that Chapter 2 summarizes a list of criteria [28] to determine if a change in MLDT has a larger impact in overall $A_o$ compared to changing MTBF. The sample data provided by the MRDB satisfies these criteria. That is, the sample data satisfies the following statements:

1. System $A_o$ is normally above 0.50 or 50%.
2. $MTBF > MTTR + MLDT$
3. $MLDT > MTTR$

Additionally, the sample data sorted by the categorical factor of homeport is also satisfied. The specific analysis supporting this conclusion is in the supplemental case study. With the promising evidence showing that a solution to this problem statement might be feasible, the research moved forward with capability and requirements analysis for the model.

### 3.2.2 MLDT Capabilities and Requirements

Conversations with the PEO IWS office for CIWS helped form the capabilities and requirements for this optimization model. The following capabilities and requirements are the foundation for trialing proofs of concept and feasibility analysis. If the POC proves feasible through a case study, then the PEO IWS office could further refine the optimization model to a higher technology readiness level, including:

1. Accessibility
2. Multi-Variable Optimization
3. Achievable Solutions
4. $A_o$ Cost Benefit
5. Data Verification and Validation

**Accessibility**

The PEO IWS office is dealing with the problem of modeling software accessibility. Matlab, and other more sophisticated modeling software, are not easily accessible without specifically contracting for them. Additionally, personnel who work in PEOs are either engineering duty officers (EDOs) or civilian NAVSEA engineers. EDOs are restricted line naval officers who may not have requisite experience with programming languages. Similarly, NAVSEA engineers that work within PEOs act at the level of program managers rather than computer programmers. The same EDOs and NAVSEA engineers have the difficult job of providing requisite analysis to higher authorities to make a logistics change to the SOI.

**Multi-Variable Optimization**

Like other systems that are managed by the USN, CIWS contains many subsystems functioning together to produce desired effects for the operators. Similarly, most systems managed by the USN are SoSs comprised of many unique parts with different failure rates, resupply rates, and costs. The optimization model must be capable of assessing more than one change in part MLDT. As mentioned in Chapter 2, part performance affects block performance, which affects overall system performance. So, the optimization model must be capable of assessing a change in part MLDT, which then analyzes the change in block MLDT, which then assesses the change in the overall system MLDT.

**Achievable Solutions**

Solutions to an optimization problem must also be achievable in that the stakeholders can implement the solution. There are two primary considerations for checking the achievability of a solution. First, solutions to the optimization model must be limited to changing logistics plans for a finite number of parts. So the optimization model must pick the most impactful parts to change rather than all of them. Secondly, the optimization model must provide the cost-benefit of making changes to the CIWS logistics infrastructure. This second requirement implies that the optimization model is capable of aggregating changes in part MLDT and estimating the overall system MLDT as a result of the logistic changes.

$A_o$ **Cost Benefit**

In a similar line of thought to **achievable solutions**, the model must be capable of providing an availability cost-benefit. Logistics changes for DON systems can cost millions of dollars. A simple solution to reducing the system MLDT would be to ensure that replaceable parts are available at all times. This change would effectively reduce the logistics delay time to zero hours. However, this change is presumably infeasible because of the cost. As a result, the optimization model must be able to balance the cost of reducing logistics delay times for parts and the improvement of the overall system availability. NAVSEA has also made $A_o$ a reporting requirement for analysis such as this.

**Data Verification and Validation**

The PEO IWS expressed specific formatting problems with MRDB data. Multiple unique part identifiers can apply to the same part. The following list gives part identification systems used for logistics management. This list is not comprehensive; however, the systems listed are generally considered the most common. Efforts to locate recent research on the reason why the DON does not use a universal standardized material identifier were unsuccessful. Commonly used part identification numbering systems are the following:

- NIIN
- NATO stock number (NSN)
- record serial number (RSN)
- DON Part Number

These unique identifiers imply that different parts serve different purposes within the SOI. However, since these large systems have significant logistics and support periods in their life-cycle, parts are replaced with new parts for various reasons. For example, a part supplier may go out of business or allow their contract to expire. This result would require the cognizant PEO to begin contracting for a replacement vendor and a potentially different part. Another example is that the failure rate of a particular part is unsatisfactory, and a new part with a lower failure rate is acquired. Since the two parts are technically different, even though they perform the same function within the system, those two parts will have different part identifiers. The PEO would like the ability to merge and consolidate parts with such issues. The PEO request is valid because the performance analysis depends on how well the system functions. If two serial numbers perform the same function within a system, then those two parts should be considered the same. With these capabilities in mind, the POC was tested using sample data from the MRDB.

## 3.3 Proof of Concept (POC)

The POC is a linear programming optimization. The optimization takes historical data, provided by NSWC Corona, and provides an availability cost-benefit analysis. The optimization selects a finite number of parts and reduces their respective MLDTs. This optimization model has key assumptions, discussed here. The POC was developed using representative data based on phone interviews and email correspondence with PEO IWS 11 and NSWC

Corona. The primary objective of this POC was to verify that an optimization model could be done based on the types of information available. This section discusses the development of the model and associated problems.

### 3.3.1 Assumptions

The biggest assumption in this POC is the format of the data. Table 3.1 is the assumed type of data available from MRDB in MS Excel format.

Table 3.1. Data Field Information for POC

| Data Field | Format | Units |
|---|---|---|
| Part Number | General | N/A |
| Nomenclature | General | N/A |
| Mean Time Between Failure (MTBF) | Number | Hours |
| Mean Logistics Delay Time (MLDT) | Number | Hours |
| Mean Time to Repair (MTTR) | Number | Hours |
| Mean Outside Assist Delay Time (MOADT) | Number | Hours |
| Mean Admin. Delay Time (MADMT) | Number | Hours |
| Historical Cost | Currency | Dollars |

The following assumptions were made for the optimization model POC.

1. Assume that, for each component in this system of interest, the cost of MLDT reduction per day is available or can be determined.
2. Assume the mean failure and logistic delay rates follow an exponential distribution. This assumption allows for MLDT parts to be calculated together in the same way as failure rates are added together for series and parallel connections.
3. Assume that an MLDT reduction budget is defined and that stakeholders want to avoid high costs for diminishing returns. This assumption implies that a Pareto curve and cost-benefit analysis may result in an optimal choice.
4. Assume prior FY state data for the system of interest is historically consistent and can be used to infer a new $A_o$ based on changes to MLDT. This assumption justifies that a change to the MLDT of a group of components will result in a change in $A_o$.

Assumption 1 is critical because it provides a mathematical relationship between changing a component's MLDT and assessing how much that change in logistics response time will cost. If the optimization model can provide a cost analysis of the MLDT change to the SOI, then an $A_o$-cost analysis becomes more feasible.

Assumption 2 gives a method for aggregating changes in part MLDT. Recall that large scale systems are complex, including redundant parts, and even redundant subsystems. The overall system MLDT must be determined, and $A_o$ recalculated to see the effect of an altered part MLDT. This POC assumed that the logistics delay rate is constant so that MLDT can be calculated and updated based on changes to part logistics delay times.

Assumption 4 is essential because it gives stakeholders a level of confidence in the optimization solution and by how much $A_o$ is projected to change. Systems with predictable operational schedules should experience relatively consistent $A_o$ values from fiscal year to fiscal year. It is not unreasonable to assume that this is the case with large DON systems like CIWS.

### 3.3.2 Model Formulation

Define **Reduction Cost** as the amount of money spent to reduce MLDT for the system of interest. Define $x_i$ as the **MLDT reduction cost per day of the *ith* component** and define $y_i$ as the number of days reduced from the *ith* component's MLDT. Then, the reduction cost becomes

$$Reduction\ Cost = \sum_{i=1}^{k} x_i y_i. \tag{3.1}$$

Reduction Cost is constrained by the established budget for improving $A_o$. The reduction cost constraint is given by

$$ReductionCost \leq Budget. \tag{3.2}$$

$y_i$ are variable cells that are changed to optimize $A_o$. Using the values of $y_i$, a new system MLDT can be obtained by recalculating the mean logistics delay rate for each component.

A new $A_o$ is obtained by using the new MLDT value and holding all other mean times constant. The primary function of this model is to maximize $A_o$ for the system of interest. With a new MLDT value, $A_o$ becomes

$$A_{o_{new}} = \frac{MTBF}{MTBF + MTTR + MOADT + MADMT + MLDT_{new}}. \tag{3.3}$$

$A_{o_{new}}$ is the objective value of the optimization model. Using the new $A_o$ relationship as an objective to optimize, the performance data can be used to create optimization constraints.

**Constraints**

An MS Excel solver was used to build the constraints of the optimization model. The constraints listed below are the constraints used for the POC.

$$ReductionCost <= Budget \tag{3.4}$$

$$MLDT_{i_{new}} >= 1 \tag{3.5}$$

$$MLDT_{i_{new}} = integer \tag{3.6}$$

$$TotalParts <= N \tag{3.7}$$

Equation 3.8 gives the objective function for the optimization model:

$$Max(A_{o_{new}}). \tag{3.8}$$

The total number of parts changed is capped by setting constraint **N** equal to a non-negative integer. For example, Setting $N = 25$ allows the solver to change the MLDT of 25 unique part numbers such that the solution may be feasible to execute. If the MLDT is reduced, then that new MLDT must be greater than or equal to one hour. This statement is a hidden assumption where MLDT cannot be reduced to zero hours. This would imply that the replacement part is already on the ship. The new MLDT value must also be an integer value. This is because most maintenance documentation is in units of hours. For example, if a 3M maintenance record is being written and it took a replacement part greater than zero minutes and less than one hour to arrive, then the MRDB would count this value as one hour.

Using these constraints, a For loop was written in Visual Basic to change the budget over a wide range and return the suggested solutions. Figure 3.1 is the for loop written for this optimization.

```
Sub MyLoop()
MyCount = 0
For InputBudget = 1000000 To 5000000 Step 250000
MyCount = MyCount + 1
Range("Budget") = InputBudget
MySolverCode = SolverSolve(UserFinish:=True)
Range("Results").Offset(MyCount, 0) = Range("Cost")
If MySolverCode = 5 Then
Range("Results").Offset(MyCount, 1) = "Infeasible"
Else
Range("Results").Offset(MyCount, 1) = Range("AO")
End If
Next InputBudget
End Sub
```

Figure 3.1. POC Visual Basic For Loop

In Figure 3.1 the MLDT reduction budget is the “InputBudget” and it nominally ranges from \$1 million to \$5 million. Each change in the reduction budget is set at \$250,000 and can be changed. The For loop solves the optimization based on the budget and constraints described above. The resulting system availability is calculated and recorded in a table. The availability-cost results for each run are plotted. Figure 3.2 shows the results of a sample optimization run.

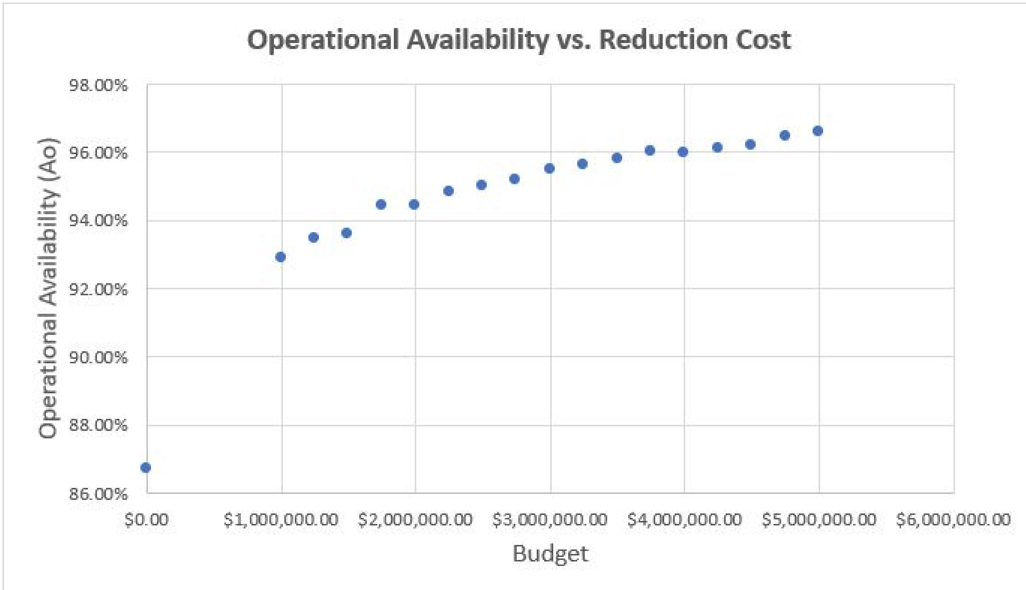


Figure 3.2. POC $A_o$ Cost Benefit

It is reiterated that the results, given in Figure 3.2, are based on mock data that is representative of data fields described via phone and email conversations [16], [31]. However, the basic response shape of the curve in Figure 3.2 is expected. It is clear to see that as the budget increases, the amount of money used to reduce the overall system MLDT increases. Since the equation for $A_o$ includes MLDT in the denominator only, it follows that a diminishing returns effect would result as the budget goes up.

An alternate view seeing the effect of the optimization solution is to graph the percentage increase in $A_o$ per unit dollar vs. budget. This graph is given in Figure 3.3. This relationship assesses how much each dollar is worth in terms of increasing $A_o$. In Figure 3.2, there was a non-linear relationship between system $A_o$ and Budget. It is expected that as the budget changes, the dollar value for changing $A_o$ also changes.

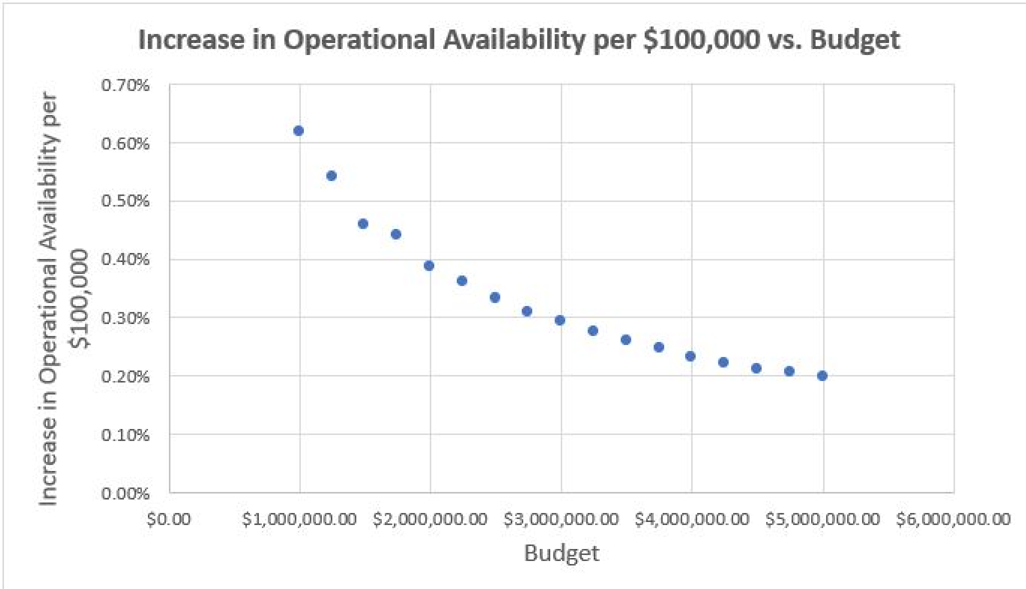


Figure 3.3. Marginal Returns Curve

Figure 3.3 shows a diminishing returns relationship for increasing $A_o$. For any system, there is greater monetary value in increasing $A_o$ when the availability is poor compared to increasing $A_o$ from a high percentage to an even higher percentage.

At this point in the POC, this research received sample data from NSWC Corona. In studying the sample data sets, the following problems arose with the formulation of the optimization model established in POC.

## 3.4 Problems with Execution POC

### 3.4.1 MRDB Accessibility

At the beginning of this research, the author and NSWC Corona explored course of actions (COAs) for accessing historical data on the CIWS system. The MRDB browser is accessible through an online browser. This web browser is accessible only through the NMCI network. For most researchers, NMCI access presents a unique problem for multiple reasons. The first reason is that NMCI access for DOD personnel who do not work in a place with NMCI work stations is difficult to obtain. For remote users, virtual private network (VPN) access is possible. However, the approval process and computer configuration instructions to obtain VPN access are complicated to follow. The author worked extensively to gain access to an NMCI VPN connection with no success.

Secondly, this research occurred during the COVID-19 pandemic. As more DOD personnel shifted schedules to teleworking, accessibility to the NMCI decreased further. According to a report from USNI News, the NMCI network can only manage 40,000 VPN connections in total [33]. This evolving requirement to telework with servers located on the NMCI network has further accentuated the inaccessibility to NMCI and its lack of infrastructure. In a recent telework user guide released by NAVSEA-03, they admit that a NMCI VPN connection has the highest complexity in terms of required assets, permissions, and protocols [34].

Thirdly, the next most straightforward way to obtain access to MRDB is to simply travel to NSWC Corona located outside of Los Angeles, CA. By traveling directly to the offices that house the MRDB, engineers can access the MRDB browser directly for the author. Unfortunately, due to time constraints in conducting research and a lack of funding, it was not feasible to travel to NSWC Corona and temporarily obtain MRDB access.

Given these issues, the easiest way to obtain sample data from the MRDB was by requesting it through correspondence with NSWC Corona engineers. This method of obtaining data presents a unique problem in that the researcher must correctly interpret the request for information and clarify missing instructions. For example, sample data had been requested over six fiscal years, from 2014 to 2019. The NSWC engineer working with the author clarified if the data was supposed to be six individual fiscal year data sets or one data set spanning six fiscal years. This example of miscommunication with requesting data alludes to a more significant underlying problem. This problem is that researchers working with the MRDB database through a proxy does not have a grounded understanding of all of the features and capabilities the MRDB browser can provide because of the difficulty in obtaining access. In an ideal world, the researcher would conduct work by viewing system data through the MRDB server and by analyzing exported MS Excel data. In reality, the author was only able to obtain exported MS Excel data and was never able to interact with the MRDB web browser directly.

These problems associated with database accessibility and usability are not unique to DON systems. Within the supply chain management field, accessibility to data, and data quality are current focuses for research. Professionals of the supply chain management field acknowledge that a higher quality of data and more accessibility is required to make informed decisions similar to those made by program managers in the DON [35]. Within DOD acquisitions, the DOD Inspector General found that, across all services, most acquisitions groups were unable to account for the status of their programs [36].

### 3.4.2 MRDB Data Validation

It was mentioned in Chapter 2 that, for each SOI, NSWC Corona engineers consolidate data from many maintenance databases into the MRDB. As the data gets consolidated, it goes through verification and validation. The data is not perfect, and illogical entries exist in the data. However, NSWC Corona makes the data as reliable as possible with the given databases that it pulls from. Issues with data are from the perspective of viewing MRDB data exported to .xlsx format. Data validity is another issue not unique to DON data systems. As with most systems that deal with big data (very large data sets), the veracity of the data is always a concern [37].

#### Missing Field Entries

Some maintenance action fields are incomplete. A sample data set of CIWS maintenance actions performed in San Diego from FY14 to FY19 was chosen to assess for missing fields. Approximately 8.74% of the maintenance actions did not document the cost of the replacement part. Similar problems exist with missing data associated with calculating $A_o$. For the same data set, logic checks for each maintenance action focused on MTBF, MLDT, and MTTR. Of all the maintenance actions performed on CIWS in San Diego between FY14 and FY 19, 39.5% of the data fields are missing at least one of the three mean values. As a MS Excel formatted file, these cells would appear blank. Some field entries are likely blank to imply that the value for that particular maintenance action is zero. For example, if a maintenance action required a replacement part and that part is already on-board in the supply department, then the logistics delay time for this situation would be 0 hours. Additionally, a blank field may indicate a value of zero.

However, for a MS Excel spreadsheet, it cannot be readily determined which entries are missing and which are intentionally blank to imply zero. The author spoke with the chief engineer about this issue and stated that MRDB data exports to .xlsx format are not perfect

[38]. In some instances, entire maintenance actions can disappear during the export process, and checks are required to ensure that the exported information is complete. So it is also possible that what appears to be an error in data entry on a MS Excel file is complete from the MRDB.

**Red Flag Field Entries**

In some field entries, the value entered appeared questionable. Of the MTBF values recorded in the sample data, approximately 3.3% of the entries include values less than five hours in duration. In some cases, a MTBF value of one hour is recorded for one fiscal year, while the next fiscal year has a MTBF value of over 100,000 hours. It is possible to have high failure rates on components. However, enough of these extremely high failure rate values raised red flags on the validity of the data entries.

**Artifacts Produce Illogical Entries**

When the MRDB exports data into MS Excel format, artifacts can appear along with values in cells where those ghost characters do not exist on the original database. For example, part identifiers like an NSN can contain a hyphen at the beginning or the middle of the character sequence. The introduction of a hyphen makes the part identifier appear unique so that categorizing data according to each part becomes impossible.

These hyphen artifacts can also appear in front of numerical values to make them appear negative. For example, artifact markings can appear in MTBF entries to make the value appear negative, which is illogical. To continue working with the data, hyphens are either suppressed or deleted. Since nearly 40% of the data contained similar errors, the following assumptions and actions to clean the data are made:

1. If an entry contained a hyphen at the beginning of the character sequence, then that hyphen was assumed to be an artifact and deleted.
2. If a value entry was left blank, it was assumed that the blank value is to mean zero.
3. If cost data were missing for a maintenance action, then it was assumed that cost data was never recorded. Those maintenance actions with missing cost data were suppressed during cost analysis.

4. Parts were categorized only based on NIIN because it was determined that this field entry contained the least number of errors and/or artifacts.

The SOI data is effectively invalidated when it is exported from the MRDB to MS Excel for the reasons listed above. Any model using data exported from MRDB is not as accurate compared to viewing calculation results directly from the database.

### 3.4.3 MRDB Cost Data

When a maintenance action is recorded and metrics are calculated by the MRDB, the record produces two types of cost data for that event: **current cost** and **historical cost** [7]. The current cost is the cost of the replacement part at the time of exporting the data. The historical cost is the cost of the replacement part at the time of the system failure. For example, maintenance data on a SOI from FY14, then the historical cost of a replacement part is the FY14 cost, while the current cost gives the part cost for the current fiscal year.

The optimization model intended to provide a cost-benefit analysis in terms of a new overall $A_o$ per dollar. If the variance in replacement part cost is high, then a cost-benefit analysis would be useless. As spare part costs significantly increase or decrease without a discernible trend, the uncertainty with an availability cost-benefit analysis also increases.

Spare part costs are assessed by viewing maintenance data from FY14 to FY19 for the following homeports:

- San Diego, CA
- Pearl Harbor, HI
- Everett, WA

For each port, the historical cost data is updated to reflect inflation from that year's data to FY19. It was mentioned earlier in this chapter that part costs for some of the recorded maintenance actions were unreported or missing. Table 3.2 gives a summary of the sample size of maintenance actions in each port in addition to the number and percent of maintenance actions that did not report cost data. It is reiterated that the cause of the unreported costing data is unknown and not the center of this research. There are too many possible failure modes for each data field error to address them in this research adequately.

Table 3.2. Unreported Cost Summary

| Port | Total Maintenance Actions from FY14 to FY19 | Maintenance Actions with Unreported Parts Cost | % of Maintenance Actions with Unreported Costs |
|---|---|---|---|
| San Diego, CA | 1427 | 108 | 7.6 |
| Pearl Harbor, HI | 390 | 34 | 8.7 |

Table 3.2 shows that approximately 7% to 9% of maintenance actions have unreported cost information. Because the failure mode for the missing data is not known, unreported maintenance actions were suppressed during analysis. The alternative to suppressing cost data is to assign a fixed value for each part. However, it was decided to suppress data because the variation in replacement part cost was determined to be both high and unpredictable. The part cost analysis was started by considering the percent difference in part costs by fiscal year.

The percentage difference between the historical cost and current cost of the same parts were calculated. The percentage difference is given by

$$Difference = 100 * \frac{C_{Current} - C_{Historical}}{C_{Historical}}. \tag{3.9}$$

For each port, a scatter plot was constructed of the percent difference in spare part cost, categorized by fiscal year. Figure 3.4 shows the percent change in part cost for all maintenance actions in San Diego, CA, from FY14 to FY19.

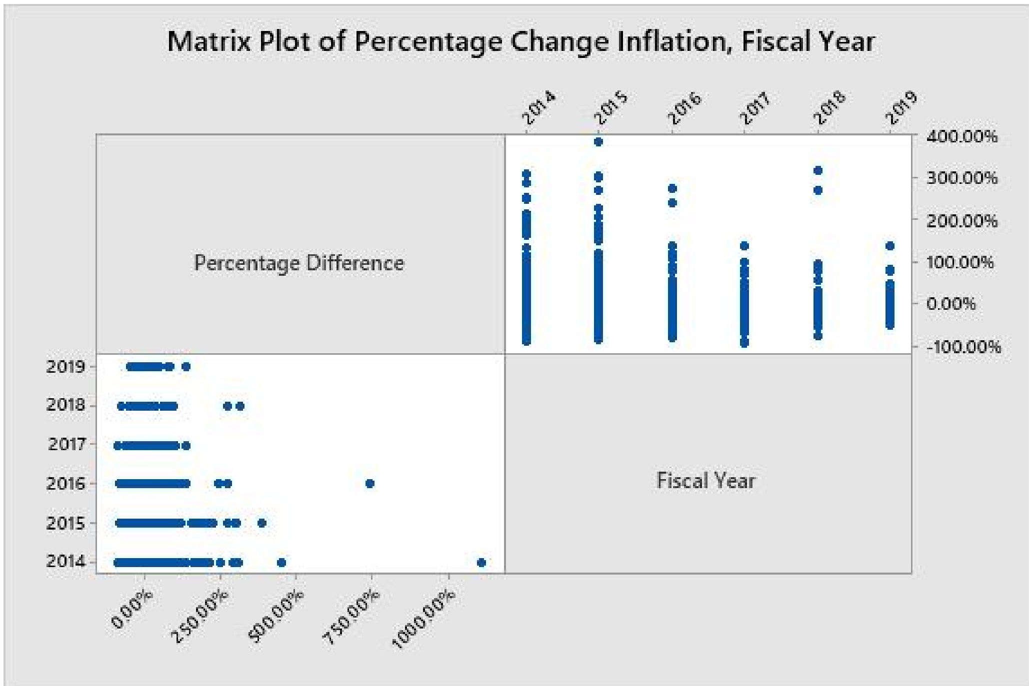


Figure 3.4. The Percent Difference in Part Cost from FY14 to FY19 for San Diego Units

Both quadrants of Figure 3.4 represent the same data with a slightly different focus on scale. The lower left quadrant represents the percent difference in part cost, by fiscal year, for all maintenance actions. This data includes outlier data points where the cost of a part increased by over 1,000%. The upper right quadrant is a scaled version of the same data with a focus on the majority of data points. With the upper right quadrant of Figure 3.4, there is substantial variation in part cost from year to year. In many cases, the cost of a replacement part can increase by 100% or decrease by over 50%. It is not clear that there is a discernible pattern in part costs over time.

A similar result is seen with maintenance data collected for all operational units in Pearl Harbor, HI. The data collected for units in Pearl Harbor are over the same period from FY14 to FY19. A matrix plot of the percent difference in part cost is given in Figure 3.5.

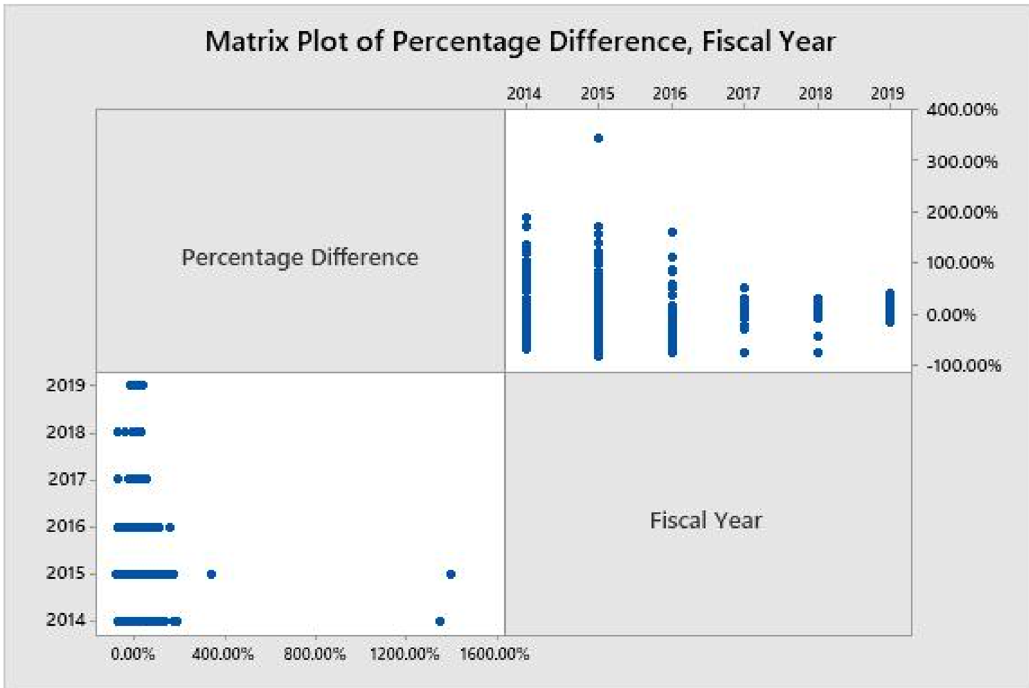


Figure 3.5. The Percent Difference in Part Cost from FY14 to FY19 for Pearl Harbor Units

The lower left quadrant of Figure 3.5 appears to have lower variance compared to Figure 3.4; however, the Pearl Harbor data set is a significantly smaller sample size. Refer back to Table 3.2. The sample size of maintenance actions in Pearl Harbor was 390, whereas the sample size of maintenance actions in San Diego was 1427.

An alternate view of cost data is to assess the confidence intervals in part cost for each port. For each port, the 95% confidence interval for the percentage difference in part cost from that fiscal year to today was calculated. The results of the two analysis of variances (ANOVAs) are given in Tables 3.6 and 3.7.

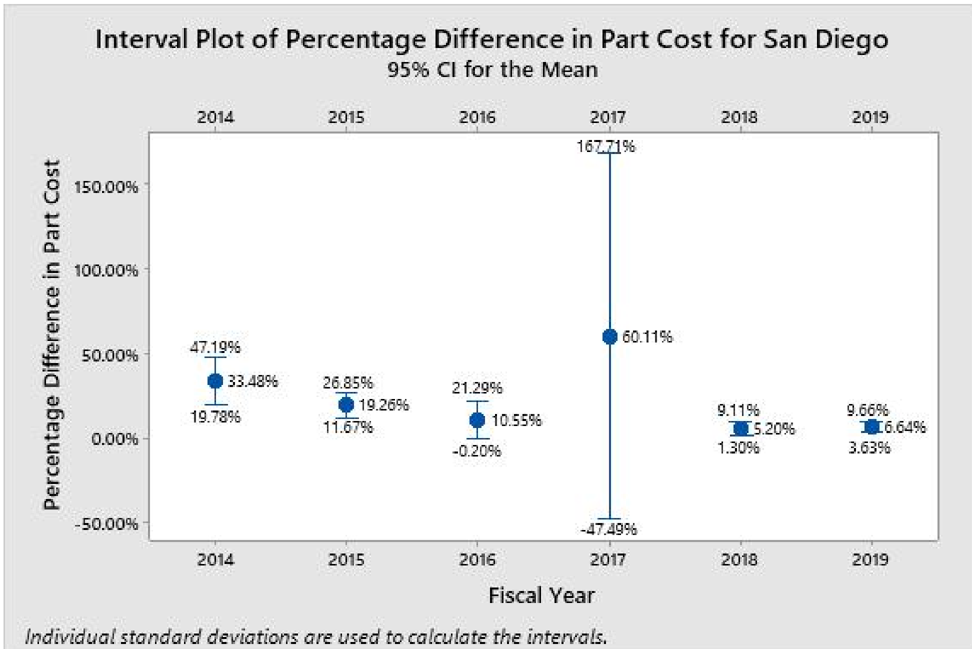


Figure 3.6. Confidence Interval Plots for Part Cost Data from San Diego

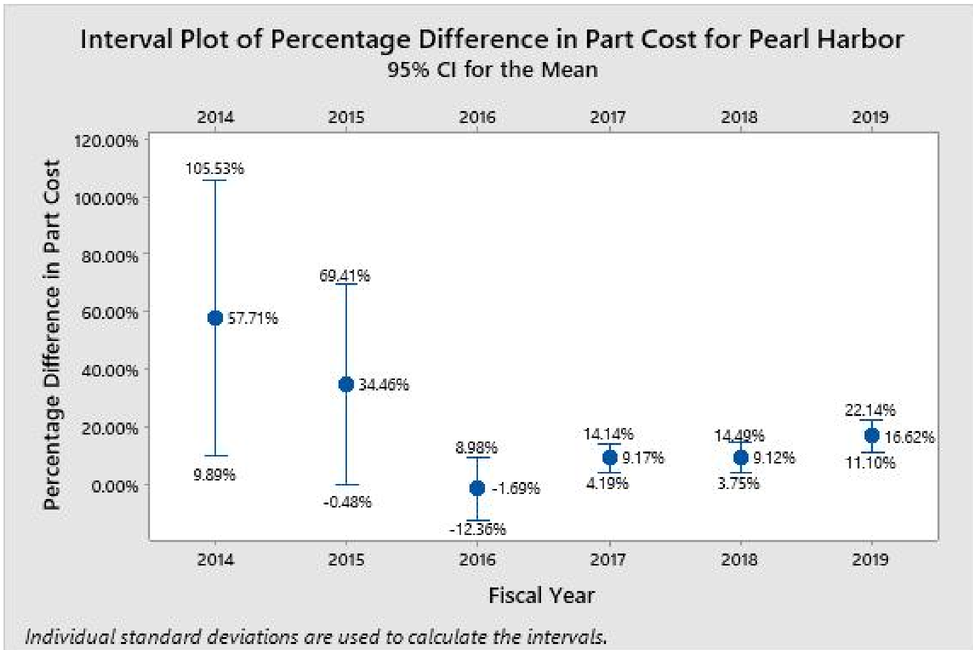


Figure 3.7. Confidence Interval Plots for Part Cost Data from Pearl Harbor

The results in Figures 3.6 and 3.7 are significantly different from each other. The confidence interval plots yield several observations. The first observation is that the variation in the difference of percentage difference in part costs was different from port to port for the same fiscal year. Secondly, the trend in the percentage difference in part cost is different for units stationed at each port. A general increase in part cost over time was expected. However, what every figure related to cost data shows is that the difference in part costs can vary both positively (cost increase) and negatively (cost decrease). In more recent years, the percentage difference confidence interval narrows. However, there is still a statistical difference from the increase in cost when comparing Pearl Harbor and San Diego. The observation that ports trend differently with changes to part cost suggests that system data should be partitioned at a lower level, such as a squadron or port, rather than globally (all together).

### 3.4.4 Part Costs are Unpredictable

Even if it was feasible to build an optimization that showed what the change to overall system $A_o$ would be due to a change in the overall MLDT, that knowledge would be worthless if the spare part costs are unpredictable. Unpredictable part costs shown in Figures 3.6 and 3.7 both increase the value of the dollar and decrease the value of the dollar. So a cost-benefit analysis without predictable spare part costs is ineffective, even for the following fiscal year.

### 3.4.5 Variance in Up-Time and Down-Time Factors

The variance of all factors that contribute to uptime and downtime were analyzed. These factors were assessed with sample data categorized by homeport and from fiscal year to fiscal year. Recall that the ratio of uptime to total time is the basic definition of $A_o$. If factors other than MLDT are relatively consistent, then a projected change in overall MLDT should result in an expected change in the overall system $A_o$. The only consistent contributor to uptime or downtime is MTTR.

Other contributors such as MTBF vary from fiscal year to fiscal year and from homeport to homeport. Enough variance exists in other factors contributing to $A_o$ that a change in MLDT does not necessarily correlate to an expected change in $A_o$. A detailed analysis of these factors is in the supplemental case study.

### 3.4.6 Static Data

Another critical issue with constructing a low-level optimization model is that SOI performance data must be exported from the MRDB servers to begin analysis in MS Excel. Exporting data from the MRDB produces static data. Any conclusions drawn from static data are valid only until new performance data is available for analysis. Maintenance action data is continually sent to NSWC Corona to update the MRDB database. Anyone who tries to build an independent optimization model that requires exported data will be forced to re-perform data cleaning and analysis to reassess the model over time.

In this case, the MRDB is at a significant advantage over analysis techniques that use static data. The performance metrics calculated using the MRDB are updated frequently due to an established process for importing and updating system data already exists. In the case of a low-level optimization model, the results of the analysis become invalid within a relatively short time as more data becomes available. There is also a lag effect of performing analysis and implementing a decision to change the SOI. When using results based on static data, it is more likely that a stakeholder will make a decision based on outdated information.

Stakeholder interviews with PEO IWS indicated that changes to logistics planning as a result of this analysis would not go into effect until FY22 or FY23. By this point, the static model would be three to four years out of date [31].

### 3.4.7 Storing Parts Does Not Imply Logistics Delay Improvement

The POC assumes that the model can give an MLDT reduction cost. This cost could be the current cost of the replacement part. However, there are significant problems associated with using current cost as the amount of money required to reduce the logistics delay time. It is assumed that the MLDT reduction cost is directly associated with reducing the logistics delay time of a specific replacement component arriving at a unit. If additional spare parts are staged at regional facilities, this will not guarantee a reduction in logistics delay time because the operational unit that requires the spare component is not always at the same port. The operational unit might be at sea, at a port different from its homeport, or its homeport. So the cost incurred of storing spare parts at regional distribution facilities would not necessarily correlate to a reduction in logistics delay time. This is especially true for situations where infrequent requests are made replacement parts due to failures in the SOI.

Another issue associated with reducing logistics delay is ensuring a part can be used by a ship's crew for maintenance when conditions require it. There are two general types of entities that perform maintenance on DON SOIs: **ship's force** and **outside technical assistance**. Figure 3.8 is a box plot illustrating which entity is likely allowed to perform maintenance on the SOI.

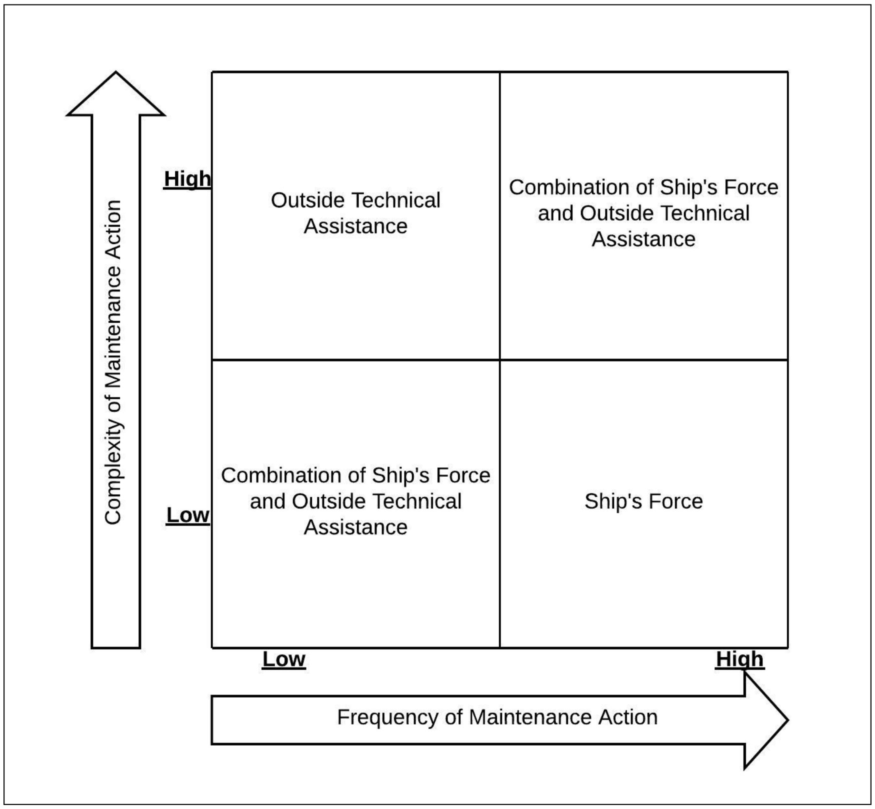


Figure 3.8. Maintenance Responsibilities

Figure 3.8 qualitatively illustrates the likeliness that the ship's crew will conduct a repair based on the complexity and frequency of a maintenance action. As a maintenance action increases in complexity, the level of technical expertise required to perform the maintenance action also increases. An increase in complexity of the maintenance makes it more likely that outside technical assistance is required to perform the work. On the horizontal axis of Figure 3.8 is the frequency of maintenance action. This axis is a qualitative representation of how often a maintenance action occurs. As the frequency of the maintenance action increases, the ship's proficiency with conducting the maintenance action increases, and the likeliness that the ship's crew will perform the maintenance without outside help improve. It is important to note that the reason for choosing outside technical assistance to perform maintenance on an SOI can vary. In some cases, the type of maintenance required is deemed to be outside of the ship's force capability. The cognizant technical authority makes this determination for the SOI. In other cases, the ship's crew have exhausted their efforts in accomplishing the maintenance and request outside assistance.

Figure 3.8 is not a universal truth for all systems carried aboard operational units within the DON. In some cases, this readiness postures and world events may require the ship's force to perform maintenance where they historically have not been allowed to do so. Figure 3.9 is a shift in maintenance responsibilities and freedoms based on changing operational environments.

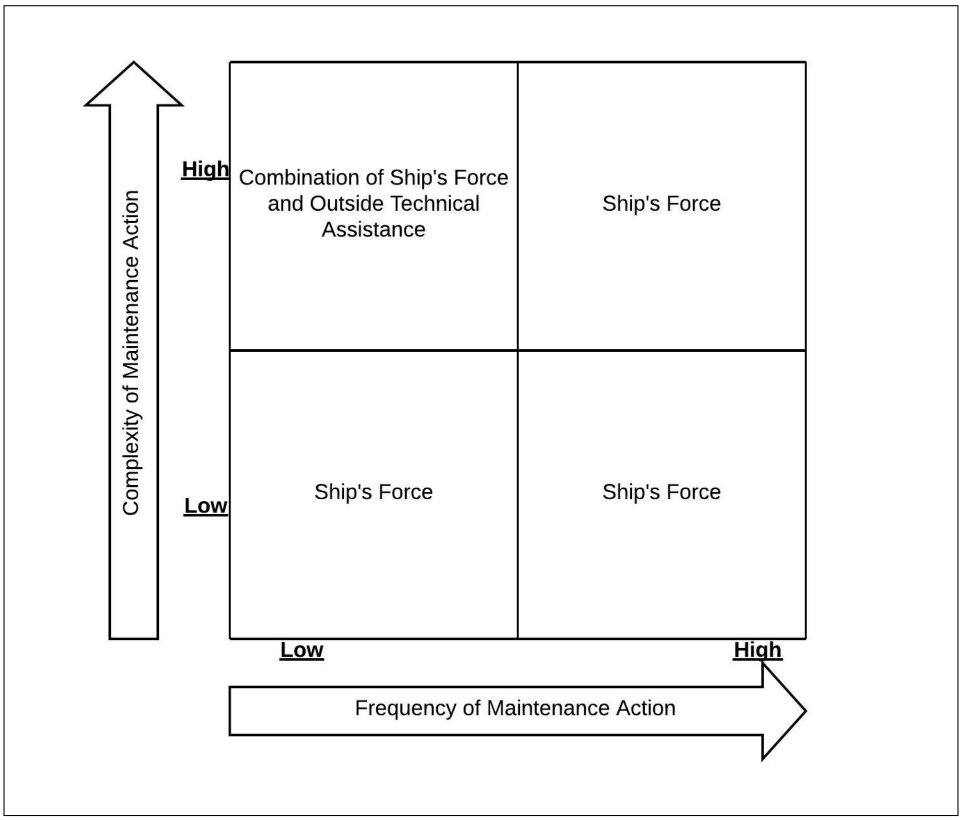


Figure 3.9. Shifting Maintenance Responsibilities Due to External Factors

Figure 3.9 shows the effects of factors, external to operational units, on maintenance responsibilities. As the need for ship's force autonomy increases, the need for ship's force to conduct maintenance that is infrequently performed or high in complexity also increases. One example of such an external factor is shifting an operational unit to a wartime footing, wherein the need for ship's force to conduct maintenance and execute missions will become a higher priority. Another situation that the DON is currently facing is the COVID-19 pandemic. The ability to send outside technical assistance to a ship is impossible if the ship is quarantined at sea. As a result, stakeholders must reassess the types of maintenance crews are allowed to perform. If maintenance responsibilities change, then the types of spare parts that are kept on-board must also fundamentally change.

### 3.4.8 The Potential of $A_o$ Impact

A performance metric called the operational availability impact, or $A_o$ impact, was identified for potential use. The MRDB defines $A_o$ impact as the amount of $A_o$ that would be added if those failure events had not occurred. Similarly, the MRDB can calculate impact of MLDT, MTTR, MLDT, and MTBF. Each unique part of the system has an associated impact value. Initially, it seemed promising to build an optimization based on which components have the most MLDT impact to the system. However, there are problems with implementing impact scores with a model.

The first reason is that an MLDT impact score cannot decrease to zero because a portion of parts ordered for operational units is due to the part not being on-board. If the parts on not on-board, then the logistics delay time must be greater than zero. So even if parts are stored at regional maintenance facilities, it will still take some time for those parts to reach the operational unit. So the overall system MLDT may be reduced, but it is unknown by how much. This uncertainty in overall MLDT change necessarily implies uncertainty in the change to overall system $A_o$. It is difficult to model a change in overall system availability based on MLDT impact. At best, parts can be ranked by logistics impact, but this component ranking is already being performed and reported [39].

### 3.4.9 Findings

At the beginning of the optimization model formulation, necessary assumptions were made about the SOI data that were necessary to check the feasibility of such a model. Many observations were made along with insights relating to the data provided by the MRDB. Critical assumptions for building an optimization model are relisted here:

**Optimization Assumptions**

1. Assume that, for each component in this system of interest, that the cost of MLDT reduction per day is available or can be determined.
2. Assume the mean failure and logistic delay rates follow an exponential distribution. This assumption allows for MLDT parts to be calculated together in the same way as failure rates are added together for series and parallel connections.
3. Assume that an MLDT reduction budget has defined, and stakeholders want to avoid high costs for diminishing returns. This assumption implies that a Pareto curve and cost-benefit analysis may result in an optimal choice.
4. Assume prior FY state data for the system of interest is historically consistent and can be used to infer a new $A_o$ based on changes to MLDT. This assumption provides some justification that a change to the MLDT of a group of components will result in a change in $A_o$.

**Assumption 1**

Assumption 1 was determined to be invalid because the fidelity in cost data was not available. There was a potential to use historical cost for spare parts to form an estimate of how much money it would cost to store or carry extra spare parts. However, Section 3.4.3 shows that spare part costs are unpredictable from year to year and from homeport to homeport.

**Assumption 2**

In Section 2.1.5, it was shown that MRDB calculates factors of system uptime and downtime using Markov chains. This assumption that overall system $A_o$ and overall system MLDT can be calculated without using stochastic modeling techniques is invalid. A change to an individual part MLDTs affects the block MLDTs. Based on the SOI reliability block diagram (RBD), the overall system MLDT is updated using Markov chains. Because of the need to conduct Markov analysis to calculate an overall system MLDT, an overall $A_o$ cannot be calculated.

With this finding, it possible to construct an $A_o$ optimization in MS Excel using on Markov processes? It is possible but challenging. The Markov process for the SOI would have to be defined based on the system RBD. Additionally, each part must be cataloged to affect a specific subsystem block so that traceability exists from individual parts to subsystem blocks to the overall SOI. The value in building a more sophisticated optimization model in MS Excel is minimal for these reasons and for the fact that the MRDB performs the same availability calculations on their server with regularly updated data.

**Assumption 3**

This assumption is not necessarily invalid. Often, PEOs must assess and rank methods for improving system performance and account for budget and time constraints. It is a reasonable assumption that a program manager would want to assess the amount of improvement in the system $A_o$ over a range of budgets.

**Assumption 4**

This assumption is invalid, shown by an assessment of sample data of the CIWS for operational units stationed in Pearl Harbor, HI, and San Diego, CA, from FY14 to FY19. A detailed analysis of the contributing factors to $A_o$ is in the supplemental case study. Of the contributing factors to overall $A_o$, the only predictable factor was MTTR. The analysis shows that a marginal change in overall MLDT is likely shadowed by other dominating factors such as overall MTBF. The result means that other contributors to downtime are driving overall availability change.

**Assumptions Conclusion**

Three of the four assumptions for this optimization model were invalid, and the invalid assumptions could not be changed to reflect the exact format of the data available from the MRDB. **A low-level $A_o$ optimization model for a SOI tracked by the MRDB is infeasible**.

## 3.5 Conclusions and Recommendations

PEOs often report on system performance through various assessments. Many of these assessments are in Figure 2.3, and they include system data analysis from the MRDB. There is a noticeable trend with how overall system performance metrics are grouped and displayed for review. In general, a SOI report groups the total population of systems together to report the overall system $A_o$. This trend implies that the $A_o$ for all systems deployed on operational units is a single result. When the entire population of systems is grouped to report $A_o$, this is called the $A_o$ of the fleet. A detailed analysis regarding the grouping and reporting of the overall system $A_o$ is in the supplemental case study.

There are dangers with reporting the overall system $A_o$ for every system as a single number. Generally, when an entire fleet of systems is grouped for analysis, the sample size increases. The overall performance of the fleet of systems averages out to a relatively consistent value from fiscal year to fiscal year. This display of $A_o$ is ineffective for several reasons.

The first reason why reporting a fleet-wide $A_o$ value is that it removes the granularity in individual SOI performance. If there is significant variation in system performance based on categorical grouping, then that granularity in the data is missing. Program managers should question how the same systems deployed around the world differ in performance based on categorical factors. The initial reliability and maintainability documentation showed that the overall system $A_o$ did not vary significantly from fiscal year to fiscal year. The observed consistency may suggest that logistics requirements are generally the same for units stationed one homeport vice another. If this suggestion becomes an assumption, then a PEO can suggest one solution for all operational units that carry their SOI. In other words, this logistics solution is a "one size fits all" answer that spans all categorical factors. This assumption, however, is not justified with analysis. A comparison of fleet-wide $A_o$ versus categorical $A_o$ values is in the supplemental case study. This leads to the second reason why an overall $A_o$ value is dangerous.

The second danger in reporting a fleet-wide $A_o$ value is that a plan to change logistics assumes that the needs for each regional maintenance facility are the same. This research is not suggesting that different analyses of $A_o$ would result in the complete, correct list of parts. There is always variance in system failure modes, types of maintenance actions, and requisitioned parts from year to year. However, data is available to suggest what portions of the SOI should be focused on for improvement based on historical data that is logically partitioned by categorical factors.

An interview with personnel at the MRDB explained that system $A_o$ had been categorized in lower levels in the past. Unfortunately, the more performance data is partitioned in a fiscal year, the lower the sample sizes for maintenance actions become. The reduction in sample size for data results in higher variance in reported $A_o$ [38] [16]. In the case of the CIWS system, there are not enough recorded performance actions in a given fiscal year to produce consistent results in terms of $A_o$. This finding combined with the requirement that the DON requires programs to assess system performance with $A_o$ [8] results in program managers to reporting fleet-wide $A_o$ results for SOIs.

The following conclusion is made based on these observations. Fleet $A_o$ reports can be misleading for reasons shown earlier. It is also clear that reporting $A_o$ based on categorical factors will most likely result in widely varying results that prevent program managers from making informed decisions on how to improve overall system performance. With these observations, it follows that a different performance metric is essential to improving system performance. $A_o$ is a performance metric that is too high-level to provide evidence to make informed decisions for a system that employs a fleet of the same system.

## 3.6 Chapter Summary

This chapter showed that a low-level $A_o$ optimization model is impractical to build. If additional complexities are incorporated, then the optimization model would recreate what the MRDB already does in calculating $A_o$ using Markov chains. Numerous examples of why it would be impractical to build an optimization model are discussed. Additionally, system performance data is viewed at the fleet-wide level with little regard for categorical factors. These conclusions show that a low-level performance metric is needed in-place of $A_o$ to investigate categorical factors and improve overall MLDT.

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# CHAPTER 4: Logistics Delay Time Reduction Method

The previous chapter explained the infeasibility of building a low-level model to optimize the overall system $A_o$ by reducing spare part logistics delay time. Chapter 3 concluded that low-level performance metrics are required to assess SOI logistics performance. $A_o$ does not give sufficient evidence to make informed choices about logistics changes to the system. Chapter 3 also showed that fleet performance data should be grouped by logically chosen categorical factors. The same system employed in different environments will fundamentally have different needs. This chapter takes the conclusions from Chapter 3 and lays out a methodology for partitioning system data and using a supply chain metric to identify problem areas to improved. The chapter gives a redacted summary of the case study done on CIWS and provides generalized conclusions.

The selected supply chain metric for this methodology is the supply chain criticality index (SCCI). This chapter begins by explaining the theory behind SCCI.

## 4.1 Supply Chain Criticality Index Theory

The SCCI is a measure to determine which component within a SOI is most likely to be ordered as a result of a failure event [40]. The SCCI is defined in [40] as

$$SCCI_i = N_i * \lambda_i * MLDT_i. \tag{4.1}$$

The SCCI is based on the following definitions.

- $N_i$ **:=** The total number of that unique part required for the SOI to operate.
- $\lambda_i$ **:=** The failure rate of the *ith* component in the SOI.
- $MLDT_i$ **:=** The mean logistics delay time (MLDT) of the *ith* component in the SOI.

The SCCI is effectively an unnormalized score to determine the most likely component to be ordered due to a failure. Equation 4.1 is used to calculate the SCCI score for each unique part in a system. As [40] explains, calculating the SCCI for a fleet of the same systems is particularly useful due to the repetitive ordering of the same parts. As the SCCI score for a part increases, the likeliness that part will need to be ordered due to a failure increases. So, as the SCCI score for a part increases, the likeliness that this part will contribute to logistics downtime also increases.

It is important to note that equation 4.1 is a unitless, unnormalized score to rank parts against each other in terms of the likeliness that a part will be ordered. Equation 4.1 is unitless because the $\lambda_i$ is in units of $\frac{1}{time}$, MLDT is in units of time, and $n_i$ is unitless. So, the units in equation 4.1 cancel out and result in an unnormalized score. Terms that are used to calculate equation 4.1 should also have consistent units; otherwise, the SCCI score will be nonsensical. It is often the case that performance data for SOIs are given in units of hours, and the SCCI score could appear to be small.

As an example, consider part **X** in a SOI. Part X has a mean time between failure (MTBF) of 10,000 hours, a mean logistics delay time (MLDT) of 100 hours, and 6 are required for system operation. Then, we have the following summarized information about the part and its corresponding SCCI score,

- $N_X = 6$
- $\lambda_X = 0.0001\ hrs^{-1}$
- $MLDT_X = 100$ hrs

$$SCCI_X = 6 * (0.0001) * 100 = 0.06.$$

The unnormalized score can appear small. The $SCCI$ score in this current form must be carefully compared to all other part scores in the system to determine which require focus. The following steps are performed to normalize the SCCI scores.

For a SOI with $N$ components, the sum of all part SCCI scores is obtained.

$$\sum_{i=1}^{N} SCCI_i \tag{4.2}$$

Each $SCCI_i$ score is then normalized by dividing equation 4.1 by equation 4.2. This operation produces a normalized score for each part that represents the percent contribution to MLDT [40],

$$\%SCCI_i = 100 * \frac{SCCI_i}{\sum_{i=1}^{N} SCCI_i} = 100 * \frac{N_i * \lambda_i * MLDT_i}{\sum_{i=1}^{N} N_i * \lambda_i * MLDT_i}. \tag{4.3}$$

Equation 4.3 gives the percent contribution to logistics delay time. Regardless of what the SCCI scores are for the SOI, equation 4.3 gives stakeholders a normalized representation of which parts contribute the most to logistics downtime.

### 4.1.1 SCCI at the Subsystem Level

The same SCCI calculations can be made at the subsystem level. For the subsystem level, consider the RBD shown in Figure 4.1.

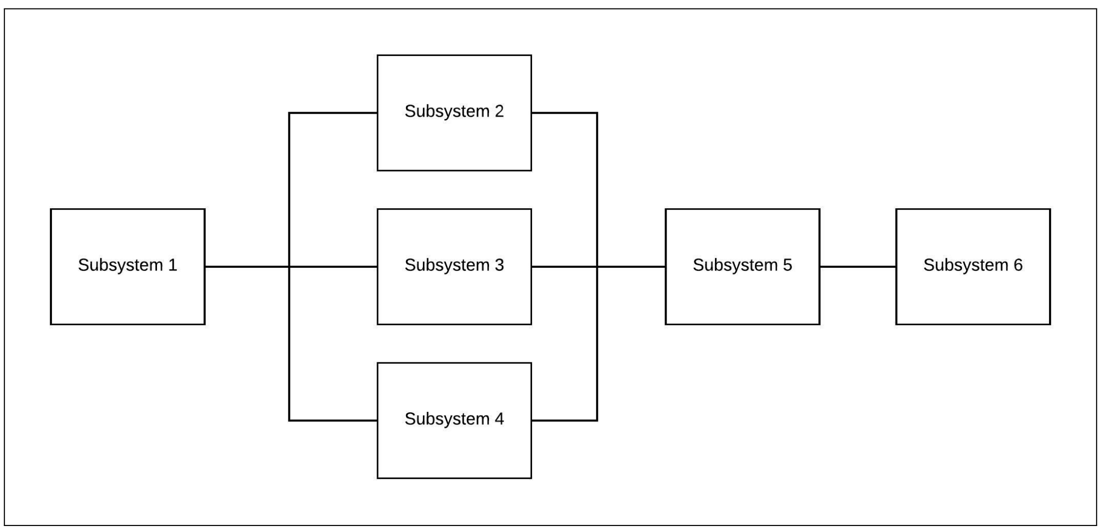


Figure 4.1. Sample Reliability Block Diagram

Figure 4.1 is an example reliability block diagram (RBD) for a SOI. Each subsystem contains multiple components with associated failure rates, logistics delay times, etc. Those part level performance metrics aggregate into subsystem level performance metrics as shown in Chapter 2. To calculate SCCI for the subsystem level, the subsystem failure rate, MLDT, and number required for operation are needed. For the subsystem level SCCI calculation, the equation becomes the following:

$$SCCI_{Block_i} = N_{Block_i} * \lambda_{Block_i} * MLDT_{Block_i} \tag{4.4}$$

The SCCI is based on the following definitions.

- $N_{Block_i}$ **:=** The total number of that subsystem block required for the SOI to operate.
- $\lambda_{Block_i}$ **:=** The failure rate of the *ith* subsystem component in the SOI.
- $MLDT_{Block_i}$ **:=** The mean logistics delay time (MLDT) of the *ith* component in the SOI.

Similarly, the percent contribution to logistics delay time for each subsystem block in the SOI is given in equation 4.5

$$\%SCCI_{Block_i} = 100 * \frac{SCCI_{Block_i}}{\sum_{i=1}^{N} SCCI_{Block_i}} = 100 * \frac{N_{Block_i} * \lambda_{Block_i} * MLDT_{Block_i}}{\sum_{i=1}^{N} N_{Block_i} * \lambda_{Block_i} * MLDT_{Block_i}} \tag{4.5}$$

This section introduced the concept of supply chain criticality index (SCCI) and how it can be used at the parts level and subsystem level of analysis. Section 4.2 discusses the necessary conditions to place spare parts on-board to reduce logistics delay.

### 4.1.2 Types of SCCI Cases

When calculating SCCI and percent SCCI at the parts and subsystem block levels, it is essential to emphasize the types and rankings of logistics delay cases. Figure 4.2 gives a quad chart representation of the types of cases that are considered.

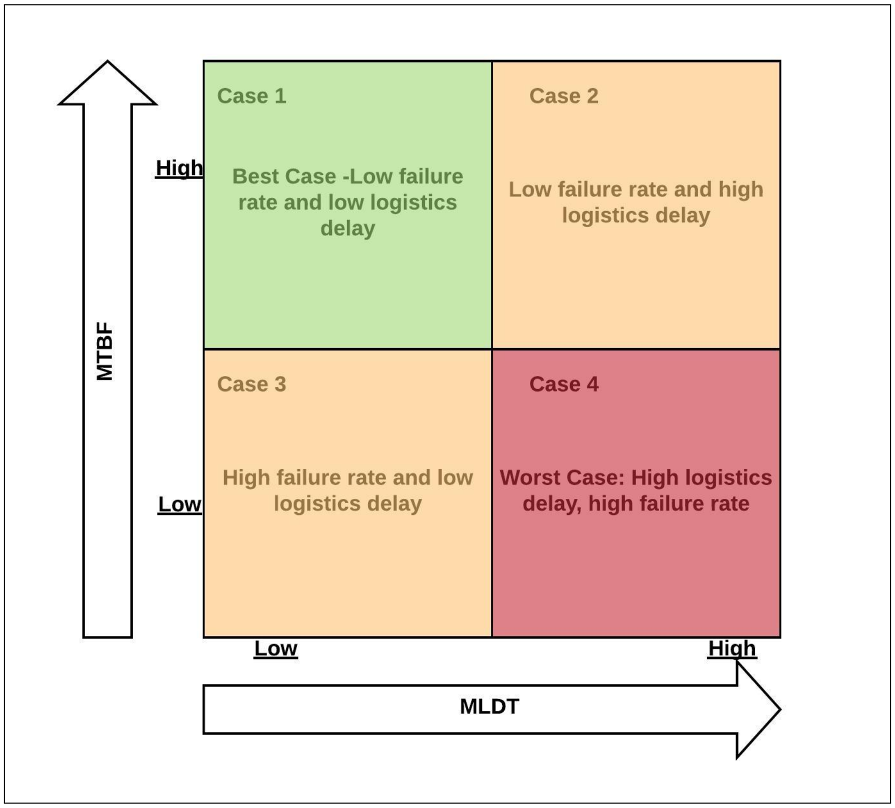


Figure 4.2. Types of SCCI cases Based on MLDT and MTBF. Green indicates the best SCCI case in terms of resulting downtime. Yellow cases result in higher downtime followed by red cases, which result in the highest downtime.

In Figure 4.2, each quadrant is color coded green, yellow, or red in terms of the amount of resulting downtime due to a failure event. Red represents the highest downtime for a system, whereas green represents the least amount of downtime for a system. Yellow is intermediate downtime between the red case and green case. Figure 4.2 can be used at either the parts level or subsystem block level. It is important to note that the number of parts or subsystems required for operation is not accounted for in Figure 4.2.

**Case 1**

For all system SCCI cases, case 1 is the best-case scenario for a failure event, with a low failure rate and low logistics delay time. This case ranks at the bottom of the percent SCCI scores.

**Case 2**

Case 2 is the problem of a low failure rate event, and a logistics delay time is very high when the failure occurs. For instance, an unexpected failure occurs for a part or subsystem with a historically low failure rate. This case results in a long logistics delay because the failed component is not likely to be stored on-hand.

**Case 3**

Case 3 is the problem of a high failure rate event for a part or subsystem that is readily available in the supply chain. Because they fail often, these events have low logistics delays.

**Case 4**

Case 4 is Red and is the worst case for a failure event, resulting in the highest amount of downtime for the system. Components and subsystems fall into Case 4 in several ways, as this is the case of the system with a high failure rate and high logistics delay. Cases that follow case 4 should addressed first in a logistics improvement process.

## 4.2 Requisite Conditions to Place Spare Parts On-Board

This section focuses on the conditions required to justify placing selected spare parts on-board operational units. The applications of supply chain criticality index (SCCI) shows promise as far as providing the most likely components to be ordered for a SOI. If stake-holders can determine the most likely components to be ordered, then those components can be vetted and placed on-board the operational unit; this method guarantees a logistics delay time of zero hours since the part would already be available. Spare parts must be stored on-board to ensure a logistics delay reduction.

1. Subsystems have been identified and tend to have high SCCI scores.
2. Parts within those subsystems are routinely ordered and not kept on-board.
3. Those parts are vetted to be usable in maintenance actions that can be accomplished by ship's force.
4. Those maintenance actions typically do not require a shipyard or regional maintenance facility to perform work.

Systems tracked by the MRDB often experience failures while on deployments away from their home ports. Section 3.4.7 explained that some maintenance actions are performed by outside technical assistance. If a part were placed on-board and it was known that ship's force could not use it, then the contribution to the system's downtime would shift from logistics delay time to outside-assistance delay time, and money would be wasted in storing that part on-board.

Another condition to account for is to ensure that the part can be used in a maintenance action that can be accomplished away from a shipyard or regional maintenance facility. It is fiscally inefficient to place spare parts on-board an operational unit if a shipyard environment is required to use that part. Common examples of maintenance actions that require a shipyard environment or regional maintenance facility are ones that require large crane operations to accomplish steps in the maintenance. Other examples of maintenance actions requiring a shipyard or regional maintenance facility are those that need specialized testing equipment and specific ship conditions that cannot be established while operating at sea.

The conditions listed in this section are the most basic requirements to justify placing a spare part on-board an operational unit. This section explains how SCCI analysis can diagnose logistics delay problems for a SOI.

## 4.3 How SCCI Analysis Should be Implemented

This section discusses the direction of analysis and commonly used metrics when diagnosing system performance. Analysis of SOI performance should begin at the system level and move down. Figure 4.3 illustrates the level of analysis and how stakeholders typically use performance metrics.

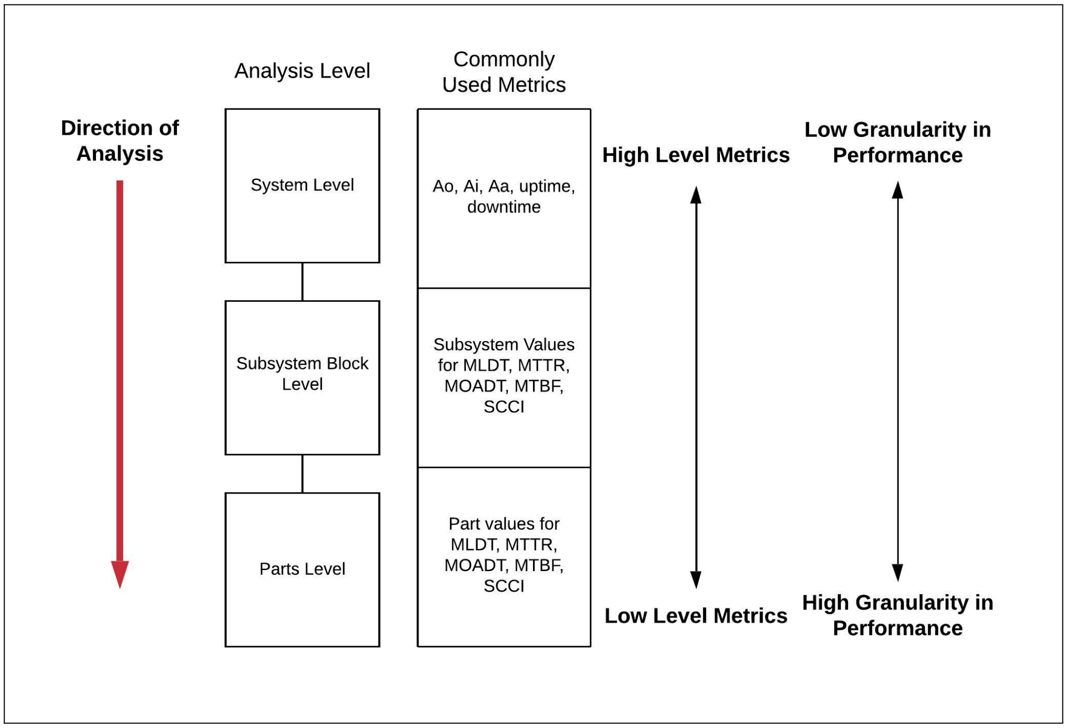


Figure 4.3. Analysis Levels and Performance Metrics. The figure shows that performance analysis should start at the system level and work down to the subsystem and part levels, resulting in higher granularity in performance as analysis moves down.

Figure 4.3 illustrates how different levels of analysis correlate with the commonly used performance metric. There are three primary levels of analysis for systems: system level, subsystem level, and parts level. System-level analysis is usually done using availability calculations. It is important to note that lower level metrics, such as MLDT, are also calculated at the system level. However, they are not the primary performance metric at the system-level. As the level of analysis goes from the system-level to the parts-level, the granularity in performance increases. As the granularity in performance increases, stakeholders have more clear evidence to make informed decisions to make changes to the SOI and its support infrastructure. For example, $A_o$ at the system level may indicate that the system is experiencing excessive downtime, and further investigation is required. This is analogous to troubleshooting a fault in a system. The indication of a fault is the inadequate $A_o$ result at the system level. To determine the contributions to downtime, stakeholders must move down in the analysis level to the subsystem level.

In large complex systems such as those tracked by the MRDB, these systems are a collection of subsystems connected in a particular configuration that corresponds to a RBD. There is a natural hierarchy in each SOI architecture where each subsystem performs one or more primary functions, which are affected by failing components. Direct measurements and lower level metrics such as SCCI are useful at the subsystem level to determine what area of the system to focus on to change in terms of any field such as system design, spare parts inventory, or logistics supply chain.

As shown in Figure 4.3, SOI performance analysis should start at the system level and move down to lower level, as this analysis direction is similar to traditional fault isolation techniques. In the case of this thesis, the fault is the observed $A_o$ value falling below an acceptable readiness value. This prompts stakeholders to investigate the reason that availability decreased below the acceptable value. With this line of reasoning, a generalized method for determining which portions of a SOI should be focused on to improve $A_o$, which focuses on improving the logistics delay contribution to downtime.

This section showed how SOI performance analysis should start at the system level and move down to the subsystem and parts level. The granularity in system performance increases as the level of analysis moves from a high level to a low level, resulting in more specific evidence for making informed decisions. Section 4.4 defines the methodology for conducting SOI analysis using the supply chain criticality index (SCCI) as a performance metric.

## 4.4 Method

This section lays out the method for analyzing SOI performance data and investigating possible solutions to improve logistics delay. This section first states the assumptions for using this method, followed by the general steps of the method. Detailed explanations of each step follow the general process and the section is concluded with general considerations when using this method.

### 4.4.1 Method Assumptions

The following assumptions are the requisite conditions for using this general method for reducing logistics delay time for a SOI.

1. Performance Data is as accurate as possible and contains all known performance information on the SOI[1].
2. Performance data has been categorized by various factors relevant to the SOI.
3. The SOI performance is being assessed by its reliability block diagram (RBD) and fundamental calculations such as MTBF, MLDT, and $A_o$ are already calculated and recorded.

Data tracked by the MRDB meet these assumptions. Any system monitored by the MRDB can use this methodology for improving logistics delay time, making it possible for this method to apply to many systems.

### 4.4.2 Method Overview

1. Determine and justify if system performance requires improvement.
2. Determine categorical factors for the SOI.
3. Select a categorical factor, determine the time interval for the SOI, and partition the data.
4. Verify Rendon-Aruna [28] criteria is satisfied using the partitioned data.
5. Calculate SCCI and percent SCCI at the subsystem level.
6. Assess and trend top contributions to percent SCCI. This indicates the top subsystem blocks that contribute to MLDT.
7. Investigate each observation and determine if MLDT would be reduced by placing spare parts on-board.
8. Provide recommendation for to the affected operational units to carry those spare parts.

Figure 4.4 gives an illustration of the generalized method.

[1]This assumption is an acknowledgement that no database for SOI performance data is perfectly accurate. Many factors such as human error, system interface errors, and variations in record keeping contribute to errors in performance data.

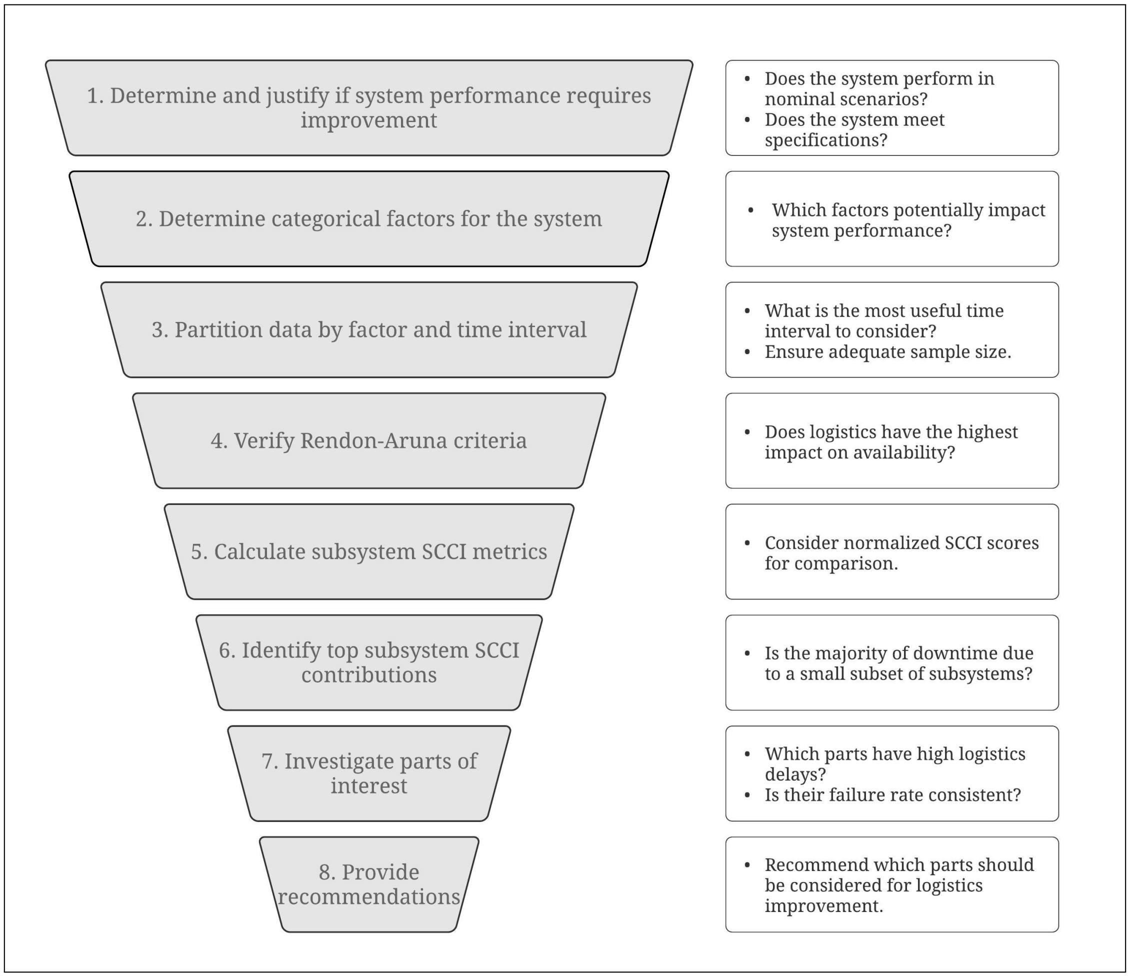


Figure 4.4. Method to Improve Logistics Delays Using the SCCI performance metric. The first step of the method is at the top of the figure and sequentially moves down. Key considerations and questions relevant to each step are to the right of each step.

Figure 4.4 shows a funnelling effect, where the number of possible replacement parts narrowed through a recursive approach. The results or output of one step directly lead to the beginning of the next step. The right side of Figure 4.4 shows key questions and comments that should be considered when conducting the step. Figure 4.4 shows that the final product of this process is to produce recommendations for specific parts in terms of logistics improvement. In this section, each step is discussed in further detail.

**Step 1: Justification**

As seen in Figure 2.1, downtime is attributed to the general areas of repair, administration, logistics, and outside assistance. An indicator in system performance alerts program managers that a change is required to the SOI to improve downtime. That is, a method to improve the logistics delay should not be used unless there is justification to do so. In Section 1.6.3, it was discussed that $A_o$ is typically not a key performance parameter (KPP). That is, an $A_o$ value by itself does not trigger a redesign of the SOI to include the logistics and support structure. $A_o$, MTBF, and MDT should be considered when assessing the readiness of the SOI. The Air Force Institute of Technology (AFIT) Scientific Test and Analysis Techniques (STAT) Center of Excellence [32] gives examples of how $A_o$ can misrepresent how well a SOI is performing in its operating environment.

Consider two SOIs that deploy at sea on-board an operational unit. Table 4.1 gives performance data for each SOI from last fiscal year's data.

Table 4.1. Example Performance Data for Two SOIs

| System of Interest (SOI) | MTBF (hrs) | MDT (hrs) | Ao (%) |
|---|---|---|---|
| SOI 1 | 4,000 | 500 | 88.9 |
| SOI 2 | 1,000 | 125 | 88.9 |

From Table 4.1, both SOIs have the same $A_o$ scores because the respective ratios of uptime to total time are the same. So, without assessing uptime and downtime, the assessment would be that both systems are at the same level of readiness. Instead of viewing performance metrics on their own, performance metrics should be compared against a nominal scenario for that SOI. For example, an operational unit can be expected to deploy for a nominal 90-day period. Assume that both SOIs are aboard the operational unit. Which SOI has higher readiness?

From an MTBF perspective, SOI 1 has higher readiness than SOI 2. Recall that MTBF and failure rate are related by $MTBF = \frac{1}{\lambda}$. Then the failure rates of the SOIs become

$$\lambda_i = \frac{1}{MTBF_i}, \tag{4.6}$$

where i is equal to 1 or 2 depending on the SOI. The reliability of the SOIs over time is then given by

$$R(t)_i = e^{-\lambda_i t}, \tag{4.7}$$

where t is the deployment length of the operational unit in days.

The associated probability of failure is $F(t) = 1 - R(t)$ and is given by

$$F(t)_i = 1 - R(t)_i = 1 - e^{-\lambda_i t}. \tag{4.8}$$

A more useful way to assess Equations 4.7 and 4.8 is by plotting the functions over time. To put the probability of failure into context, consider Figure 4.5 which illustrates the probability of failure for each SOI over the deployment period.

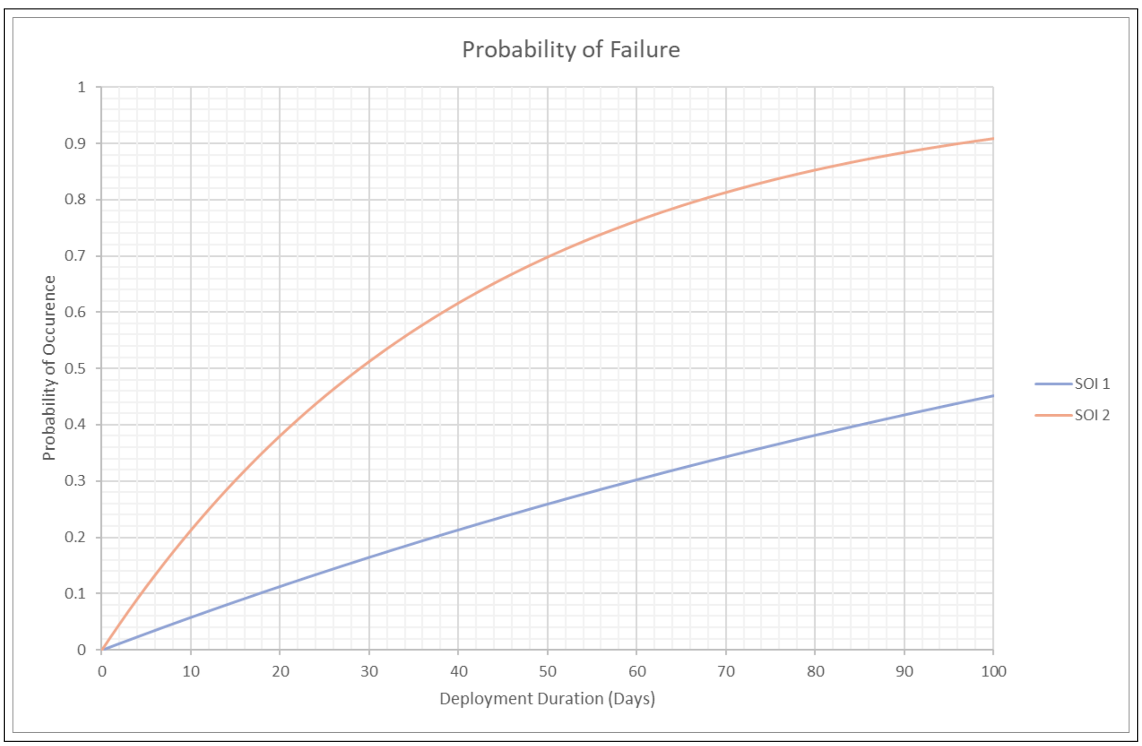


Figure 4.5. Probability of Failure Occurrence Over Deployment Period

Figure 4.5 shows that SOI-1 has a lower probability of failure at any time in the deployment compared to SOI-2. However, the probability of a failure occurring for SOI-1 increased to approximately 42% by $t = 90$. Assessing MTBF and the expected time the SOI should operate is one way to assess if the SOI should be redesigned. Another way to assess the SOI is through MDT. Table 4.1 shows that the MDT for SOI-1 is considerably higher than SOI-2. For SOI-1, this high MDT implies that the system is likely to be unavailable for 500 hours or approximately 20.8 days. Similarly, for SOI-2, the system will likely be unavailable for 125 hours or approximately 5.2 days. From a system restoration perspective, SOI-2 has a higher readiness than SOI-1. For SOI-1, 20.8 days of downtime is $100 * \frac{20.8}{90} \approx 23.1\%$ of the deployment period. If SOI-1 experiences a failure event towards the second half of the deployment period, then it is more likely that SOI-1 will be unavailable for the rest of the deployment. From a downtime perspective, SOI-1 has more risk than SOI-2.

This form of analysis must be performed in addition to focusing on $A_o$. $A_o$, MTBF, and MDT should be studied and determine the likeliness of system failures for planned deployments. $A_o$ by itself is insufficient to assess the readiness of a system to perform a mission. Expected deployment lengths, failure rates, and average downtime must be evaluated to make an informed opinion on how adequately the SOI can execute its missions for the planned deployment. Once this assessment has been done for the SOI, and it has been determined that MDT requires improvement, then there is sufficient justification in performing this methodology.

**Step 2: SOI Specific Categorical Factors**

Categorical factors are important to fleets of systems where nearly identical copies of the same system operate in different environments. It follows that if factors are affecting a fleet of systems in different ways, then that factor must be accounted for to tailor a logistics solution for the fleets of systems. Logical arguments should be used to justify that a certain factor has a significant impact on the SOI. Additionally, there is no universal list of categorical factors that should be considered for every SOI. A command and control system has a fundamentally different set of factors that should be considered compared to the CIWS. Within the realm SOIs carried on-board operational units, there are some general factors that are essential to consider.

The first factor is homeport and regional maintenance facility considerations. Within the

DON, fleets of systems are supported by regional maintenance facilities, shipyards, and parts warehouses. It is reasonable to suspect that the capabilities of the logistics and support infrastructure for the DON vary by geographic locations. For example, the logistics delay time for a SOI stationed in Everett, WA, may be different from operational units stationed in Pearl Harbor, HI, or San Diego, CA.

The age of the SOI is another factor, as aging systems within a fleet tend to experience higher failure rates compared to younger systems. A factor based on age groupings of the same system may show different characteristics and failures and logistics delays. For example, older systems may experience more failures in components with historically low failure rates. These failure events can result in extended logistic delay times because that part is rarely ordered or kept in stock at parts warehouses. While not empirically proven, this is a logical argument that suggests a categorical factor may be worth investigating.

It is also crucial to identify external drivers that dominate SOI performance due to extenuating circumstances. For example, as the author is preparing this thesis, the COVID-19 pandemic is occurring around the world. The DON must navigate the problematic trade-space of maintaining readiness while ensuring personnel safety and health amid an epidemic. It is feasible to guess that some operational units will experience extended deployment periods as a result of the pandemic. Outside technical assistance visits at sea may also be affected by the current health crisis due to quarantine concerns and maintaining the health of the unit's crew. Extenuating circumstances such as these are essential to identify so that the observed SOI performance can be studied and understood.

Other examples of potential categorical factors are ship class, squadron association, deployment area, and overall deployment length. Some form of stakeholder analysis is required to determine categorical factors that affect system performance. Furthermore, each stakeholder has different perspectives on the dominating factors for system performance; therefore, obtaining stakeholder input is essential in determining logical arguments for categorical factors.

**Step 3: Partitioning Data**

Once a set of categorical factors are determined, and those factors are available in the data, system performance data can be partitioned by factor and time interval. For example, the MRDB can group system performance data by homeport and calculate homeport level availability calculations. So it was verified that the factor of homeport could partition the performance data.

The time interval is another critical consideration in partitioning data. The recording method of performance data and the SOI dictates the time interval. For example, the MRDB primarily takes data input based on maintenance records from the 3M program. If a SOI has a low number of corrective maintenance actions that occur in a fiscal year, then it may be necessary to expand the time interval. Conversely, if a system is prone to failure and a very high number of corrective maintenance actions occur, then it could be appropriate to shorten the time interval. Another consideration is to divide performance data when the program budget for the SOI is updated. For many programs, this occurs every fiscal year. The subject of time interval selection for SOI performance analysis is a topic for future work.

**Step 4: Criteria Verification**

Once the performance data is correctly organized by a categorical factor and divided over the selected time interval, the next step is to ensure that the Rendon-Aruna criteria [28] is satisfied. Recall from Chapter 2 that if the data satisfies the criteria then MLDT has a higher elasticity than MTBF. That is, a change in overall MLDT has a more significant effect on overall $A_o$ compared to the same relative change in over all MTBF. The criteria is given below for reference.

1. System $A_o$ is normally above 0.50 or 50%.
2. $MTBF > MTTR + MLDT$
3. $MLDT > MTTR$

If step 1 was justification to begin this method, then this step is the rational justification to calculate SCCI. If the performance data satisfies the Rendon-Aruna criteria, then there is sufficient justification for seeking to improve MLDT because the criteria show that MLDT has a higher elasticity than MTBF. This set of rules is important to consider after a categorical factor partitions performance data. Once performance data is partitioned into smaller subsets of data, the data may no longer satisfy the criteria. So, it is important that the performance data, with the categorical factor, applied, still shows that MLDT has a higher elasticity than MTBF.

Confidence intervals should be used to ensure that system $A_o > 0.5$. Criteria items two and three can be shown using two-sample hypothesis tests. It is recommended to use the student t distribution to account for small sample sizes. Additionally, an $\alpha$ value of 0.05 should be used because it is the most common value to ensure a statistically significant inequality.

**Step 5: SCCI Calculations**

In Section 4.1, the SCCI and percent SCCI calculations were discussed in detail. SCCI calculations should be done at the subsystem level in the effort of diagnosing, in which portions of the SOI are the greatest logistics offenders. The percent SCCI calculations rank subsystems in terms of their contribution to overall MLDT. It is important to emphasize that the percent SCCI calculation is a normalized value that compares the contribution to MLDT, whereas SCCI is an unnormalized, unitless value.

**Step 6: Assess and Trend**

Once the percent SCCI calculations are complete, the normative values are used to assess for patterns and trending. The author recommends investigating the top subsystem blocks in terms of their percent SCCI scores and determine if those subsystems make up the majority of logistics delay time. If this is the case, then the analysis suggests that a small subset of subsystem blocks are responsible for logistics delay and that efforts to improve MLDT can focus on specific areas of the SOI. If the percent SCCI scores distribute evenly among subsystem blocks, then it would be challenging to determine where efforts should be focused.

Other questions that should be considered in this step relate to the categorical factor(s) used. Did the categorical factor change the percent SCCI results for the SOI? If there is a difference, it may suggest that the categorical factor may influence SOI performance. This implies that different solutions are required to improve MLDT based on the categorical factor used.

**Step 7: Investigate**

Once subsystem blocks have been identified and trends have been established, it is vital to investigate the validity of these findings. An effective way of reducing logistics delay time is to ensure that operational units carry commonly ordered parts as a result of a failure. This ensures that when the failure event occurs, the part is immediately available for use. To determine which parts should carry, it is recommended to calculate SCCI and percent SCCI at the parts level for the subsystem in question, or directly view the events that contributed to the logistics delay of that subsystem. For example, if a subsystem is determined to be in the top five percent SCCI scores for each time interval, then the performance data for that subsystem can be viewed to look for parts ordered. This process may yield a concise list of parts that are consistently ordered due to failures and are not kept on-board. Additionally, it is necessary to verify that these parts are able to be used for maintenance while on deployments.

If a part is routinely ordered as a result of a failure and the conditions to conduct maintenance require a maintenance facility or shipyard, then it is not useful to keep the spare part on-board. Any list of prospective spare parts must be vetted to ensure that they can be used in the event of a failure. If the maintenance action is too complex or the conditions to conduct maintenance require a maintenance facility, then the spare part should not be kept on-board. An effective way of performing this vetting is by consulting operational units that use the equipment in addition to the SOI technical authority.

**Step 8: Recommend Courses of Action**

To make use of the analysis performed, COAs should be recommended to the program manager that attempts to improve the MLDT of targeted subsystem blocks. This analysis should also consider the effects of different categorical factors and whether those factors affect the subsystem level performance. Program managers should interface with the supply corps to determine if they oppose the recommendations based on unconsidered factors. Additionally, this analysis should never suggest a new overall $A_o$ value as a result of the change in logistics planning. Chapter 3 showed that $A_o$ forecasting is not practical at a low-level, and this chapter shows that $A_o$ is misleading when assessing SOI readiness.

### 4.4.3 Limitations to the Method

It is important to note that operational units routinely carry spare parts for their systems. This practice is done for several reasons. Some of these reasons are as follows:

1. Spare parts are required for preventative maintenance.
2. A spare part was ordered for corrective maintenance and was no longer needed.
3. Operational units ordered multiple of the same spare part for anticipated future use. Multiple identical spare parts may be ordered to carry extra spares due to recent failures.

This list of reasons is not all-inclusive. However, the list illustrates a potential problem with keeping additional spare parts on-board due to their logistic impact. If each SOI on an operational unit has spare parts kept on-board for future maintenance actions, then available space becomes a limiting factor. Some ship classes can accommodate more spare parts than others. Higher-level integration with supply corps planning is required to solve this issue and is a topic for future work. Another consideration to keep in mind is that this analysis method can justify a SOI redesign. The technique can suggest likely parts that should be on-board the ship. If the majority of parts cannot be placed on-board or do not apply to at-sea repairs, then logistics delays cannot be improved without a system redesign.

This diagnostic method does not calculate or predict future system $A_o$ based on changes in logistics delays at the parts level. This chapter has shown that $A_o$ does not imply readiness for the warfighter. This method can diagnose logistics problems and investigate the causes of logistics problems using easily accessible software. The trade-off for using easily accessible software is that stochastic simulations for a system of systems are infeasible.

This section discussed the SCCI calculation and a method for using SCCI as a way to diagnose subsystems and parts that contribute the most to logistics delay. These calculations are low-level and can be implemented using MS Excel or other similar spreadsheet software tools. SOI readiness and justification were also emphasized in the first step of this method. Adequate understanding on SOI readiness is required to justify improving the logistics delay of a SOI. The next section gives a redacted summary of this method applied as a case study to the CIWS program.

## 4.5 Case Study: Redacted Summary

This section discusses the case study of the Phalanx CIWS Block 1B. The complete case study is unclassified controlled information, FOUO, distribution statement D, and can be accessed by contacting the NPS Dudley Knox Library. The Block 1B variant of the CIWS performs two primary missions: Anti-Air Warfare (AAW) and Anti-Surface Warfare (ASuW). The primary mission of AAW is only considered here. Chapter 4 of the main thesis document is used as a guide for conducting the case study. Here, the methodology of Chapter 4 is applied to performance data obtained by the MRDB.

The MRDB provided sample data for this research, giving six fiscal years of data for operational units stationed at three homeports. The three homeports requested were the following:

- Everett, WA
- Pearl Harbor, HI
- San Diego, CA

The following list are the filters used to perform data pulls from the MRDB.

1. Time frame: FY14 to FY19
2. Location: Everett, San Diego, Pearl Harbor
3. Platforms: All
4. Data Sources: 3M, CAS
5. Demand Factor is included in subsystem block metrics
6. Recorded Failure Types: Critical, Major
7. NOTE: Ship availabilities are excluded from data.

Using the list of filters to obtain system performance data, metrics for individual ships and overall homeports were calculated by the MRDB for data export. The author formatted the data and used Minitab and MS Excel to perform statistical analysis. The categorical factors of fiscal year and homeport were considered during this analysis. The method, as outlined in Figure 4.4 was used to perform the analysis. General findings are summarized here and organized by method step.

### 4.5.1 Readiness

Documented MTBF specifications and nominal mission scenarios were used to assess the readiness of the CIWS. Availability results by homeport and operational unit have a significantly higher variance compared to the overall fleet availability results. The fleetwide performance results suggest that the $A_o$ is gradually increasing. From the perspective of the operational unit level and homeport level, this is not the case. From a specifications perspective, the CIWS program outperforms MTBF requirements. Reliability specifications are not divided into threshold and objective categories. As a result, listed MTBF specifications are assumed to be threshold requirements. Without objective requirements, assessing system readiness becomes difficult. From a nominal mission scenario, CIWS fails to perform as expected. This result shows that $A_o$ is deceptive because it is a time independent ratio. To achieve a minimum passing rating in the nominal scenario, the overall MTBF of the system must be increased by a factor of approximately 2. Additionally, it was identified that the gradual increase in overall $A_o$ is likely due to a decrease in active system time. The mission scenario portion of this step suggests the need for continuing efforts to improve the system.

### 4.5.2 Categorical Factors and Time Intervals

The performance data was tagged with the following categorical factors:

1. Homeport
2. Unit
3. Unit Class

Of the three categorical factors, the research focused on homeport over the fiscal years of FY14 to FY19. The categorical factor of homeport by fiscal year resulted in an adequate sampling of performance data. When assessing unit and unit class, the sample size of maintenance actions was too few to build meaningful confidence intervals. This research uses the time interval of a fiscal year so that RMA report findings could are comparable with this analysis. The assumption that the time interval that a fiscal year is appropriate was not proven. The performance of this system may require a time interval that is not a fiscal year; however, this research leaves this topic for future work.

### 4.5.3 Rendon-Aruna Criteria

With data categorized by homeport, the performance data satisfied the Rendon-Aruna criteria [28]. That is, the data satisfied the following:

1. System $A_o$ is normally above 0.50 or 50%.
2. $MTBF > MTTR + MLDT$
3. $MLDT > MTTR$

This finding showed that MLDT at the homeport level has a higher elasticity than MTBF. This implies that a change in logistics delay will have a greater impact on $A_o$ compared to the same relative change in MTBF. The finding gives justification for using supply chain metrics to improve logistics delays.

### 4.5.4 SCCI Calculations and Trending

Normalized SCCI values were calculated at the subsystem level for each homeport and fiscal year. The top five contributing subsystems were considered for trending. For each homeport-fiscal year combination, the top five subsystems accounted for at least 75% of the overall MLDT. This finding suggests that a small subset of the CIWS subsystems should be considered for logistics improvements. Additionally, subsystems that trended in one homeport also trended in at least one other homeport. This suggests that homeport has no discernible impact on logistics delays. The SCCI trending process identified five subsystems to investigate at the parts level.

### 4.5.5 Parts Investigation and Recommendation

All maintenance actions from FY14 to FY19 were aggregated into a single MS Excel spreadsheet. For each part and fiscal year, the average logistics delay, percent NoB, and total quantity ordered, were calculated. The author selected parts of interest based on these calculations. Seventeen parts were identified and flagged for additional analysis. For each part, the percent NoB, average logistics delay, demand rate, and MTBF confidence interval were assessed to determine if the part was a potential candidate to be placed on-board operational units. Of the seventeen parts flagged for investigation, six parts were identified as potential candidates. The analysis also showed that most parts exhibited unpredictable failure rates, making it difficult to predict when a part will need to be replaced. Additionally, the author compared these parts identified with the PEO RMA report's top 10 supportability drivers. Each part listed in the top 10 supportability table of the RMA report was identified with this method and the SCCI calculation. Additionally, the parts investigation found that many of the logistics initiatives started by the PEO IWS have been working. In general, high demand parts experience little to no logistics delays and are consistently on-board. As a result, the majority of parts that contribute to logistics delays either fail unpredictably, or are low in demand. This result suggests that the logistics delay time for the CIWS system is approaching a minimum value.

If logistics improvement is approaching a limit, then other downtime factors and reliability factors should be considered. The second leading downtime factor for the CIWS program is MAdmDT and it is recommended to investigate this factor for improvement.

## 4.6 Chapter Summary

This chapter discussed the topic of supply chain criticality index (SCCI), and a method to use SCCI as apart of a methodology. Percent SCCI is a simple calculation implemented at the subsystem and parts level. It provides stakeholders with a relative contribution to overall MLDT. General assumptions and criteria described justifying the use of SCCI as a performance metric for improving MLDT problems. This method requires a readiness assessment strategy where nominal scenario performance and existing specifications drive assessment. This readiness assessment is a logical sequence of questions to determine if the SOI can perform as expected in a nominal operating environment.

This chapter also summarized the findings of the CIWS case study. The case study validates the method and SCCI calculations by comparing results of the method with the PEO CIWS RMA report. The method resulted in six candidate parts to be considered as on-board replacement parts.

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# CHAPTER 5: Conclusions and Recommendations

This chapter discusses the conclusions of this thesis and outlines topics for future work. The conclusions section is divided between two sections: **Primary research question** and **secondary research questions**. This chapter reviews the primary and secondary research questions and summarizes the key findings of this thesis. This thesis finds that low-level optimization models for system $A_o$ are infeasible. Further investigation shows that the DON overemphasizes the importance of $A_o$ as a performance metric. This assertion implies that the DON needs an overarching analysis method capable of assessing system readiness and diagnosing downtime problems. This analysis method is developed in chapter 4 and summarized here.

## 5.1 Conclusions

This section discusses the conclusions of this thesis by first reviewing the research questions given in Chapter 1. Recall that the primary research question of this research is on the feasibility of a low-level optimization model for $A_o$. This thesis finds that an optimization model is infeasible and then develops a diagnostic method for improving logistics delays based on previous research. Next, a discussion of the successes in answering the research questions is provided. Finally, a summary of the overall contributions of this thesis is presented, including information on the supplemental case study.

The primary research question is the following:

1. Operational availability is the primary metric for assessing system readiness in the DON. Is it feasible to construct a low-level optimization model that reduces logistics downtime and increases the overall $A_o$ of a system?

Secondary questions in support of the primary research question are the following:

1. If a low-level optimization model is infeasible, are there supply chain performance metrics designed logistics downtime of a system?
2. What conditions are necessary to implement such a performance metric?

3. How would the methodology for implementing the performance metric be structured?

### 5.1.1 Primary Research Question Conclusions

Chapter 3 shows that a low-level $A_o$ optimization model is infeasible. When the MRDB exports data to MS Excel, or similar, it loses validity due to data entry issues. Furthermore, when the MRDB exports data for independent analysis, that performance data becomes static. Decisions made to logistics planning based on outdated analysis are unqualified decisions. The MRDB has a unique advantage over any model that uses static data in that system performance data is constantly imported to their databases, resulting in frequently updated performance metric calculations. Chapter 3 also shows that RMA reports give fleet-level readiness and $A_o$ results without mentioning the variance in performance at the fleet or operational levels. When assessed at lower levels, the CIWS performance data shows the increased variance in $A_o$ to the point where direct performance measurements are required. Additionally, the variance in replacement part costs is inconsistent with inflation and requires further analysis. Any cost-benefit analysis for logistics improvement using current replacement part cost data is invalid without reliably predicting what the replacement part cost will be in the future. Lastly, Chapter 3 shows that Markov chains specific to the SOI RBD are required to calculate the overall MLDT as a result in changes to individual part MLDT. This observation implies that an MS Excel optimization must have the same architecture that already exists in the MRDB. Because of these observations, the primary research question is infeasible. However, useful observations and conclusions made during the development of this optimization model can apply to the secondary research questions.

### 5.1.2 Secondary Research Conclusions

The supply chain criticality index (SCCI) is a useful supply chain performance metric for diagnosing logistic delay problems by incorporating it as part of an analysis method for recommending which replacement parts should become on-board replacement parts. The supplemental case study applies this method to CIWS performance data. The case study result matches the top 10 supportability driver parts, given in the FY18 PEO RMA CIWS report. The case study finds that the method and SCCI identify all parts listed in the top 10 supportability driver list. Additionally, the method successfully investigates and recommends six additional parts for consideration. The comparison of the PEO RMA results and case study results proves the method's efficacy.

The method in Chapter 4 also states the requisite criteria at various stages in the method, stating the conditions to continue the method. The SOI analysis must contain a readiness assessment to justify investigating for logistics improvements. A SOI readiness assessment should include SOI reliability, logistics performance, and what mission scenarios the SOI should survive. To use the SCCI, the data must satisfy the Rendon-Aruna criteria given in Section 4.2. A superfluous analysis is avoided in this method because the method forces the use of checkpoint steps

Chapter 4 and the supplemental case study solidifies the structure of the method and how to use the SCCI. Figure 4.4 gives a short sequence of steps, along with key considerations, to conduct the analysis and is restated here as Figure 5.1.

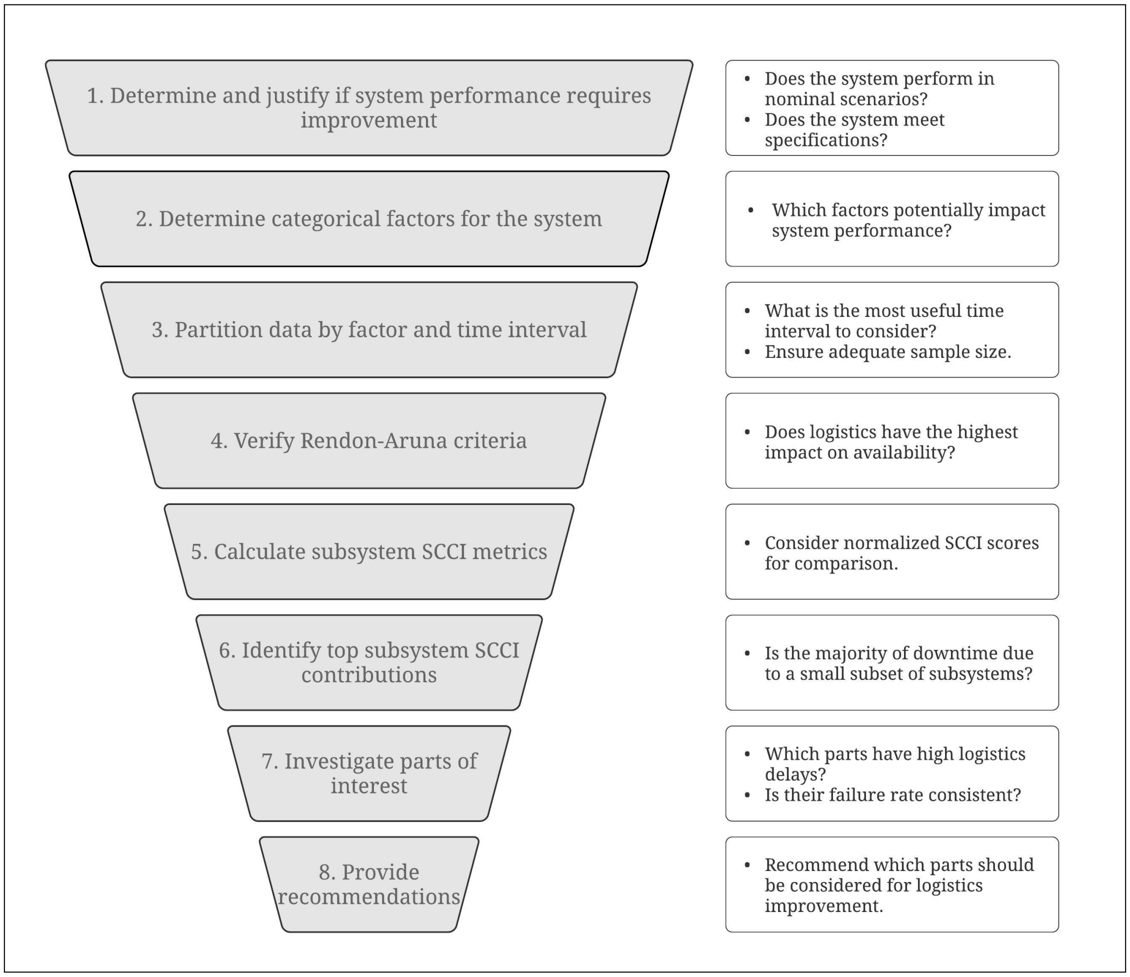


Figure 5.1. Method to Improve Logistics Delays Using the SCCI performance metric. The first step of the method is at the top of the figure and sequentially moves down. Key considerations and questions relevant to each step are to the right of each step.

The method described in Figure 5.1 applies to any system tracked by the MRDB. Additionally, SOI databases that satisfy the conditions listed in Chapter 4 can also use the method. The analysis method developed in Chapter 4 is not without limitations. The analysis method utilizes low-level performance metric calculations to diagnose logistics problems. As such, it cannot calculate the overall system $A_o$ as a result of a change in logistics delay time. Chapters 3 and 4 show that such an optimization is infeasible and that system readiness should not be solely concerned with $A_o$. While the method effectively diagnoses logistics problems, it does not predict how availability will change. Additionally, the analysis method should be re-performed annually, and as changes occur to SOI reliability or logistics. Changes to reliability and logistics metrics imply that the top subsystem SCCI contributors may change, resulting in a new set of replacement parts to investigate. This iterative process is not necessarily a negative attribute of the method. As logistics delays are improved, the method will show that those problem parts contribute less to MLDT, resulting in a new set of subsystems as the top SCCI contributors.

## 5.2 Future Work

This section describes the topics for future work that are related to this research. Several research questions appeared during this research that went beyond the scope of the primary and secondary questions. This section briefly describes each topic.

### 5.2.1 Spatial Constraints of Operational Units

The analysis method in Chapter 4 is a technique for suggesting replacement parts to be placed on-board operational units to reduce logistics delays. A significant constraint to operational units is the available space on-board. The interactions of different systems carrying different parts would become an issue. A truly integrated solution to describing which replacement parts should be stored on-board must include an analysis of available space, prioritization of parts, and an assessment of the projected operating environment. If no method for prioritizing systems exists, then the individual crew must prioritize parts.

### 5.2.2 Direct Measurement of Logistics Performance

Most performance databases within the DON indirectly measure logistics performance through 3M reports. Operational units produce and send these reports to the MRDB. This form of performance measurement is indirect because it depends on historical maintenance records to imply logistics delays. This form of measurement does not explain why some logistics delays are worse than others. A direct measurement policy would give higher granularity to why logistics delays occur with cases where parts are shipped to the operational unit. For example, the shipping industry uses big data and bar code tracking in determining transit delays between each node in a package's journey. Could the same process be applied to DON logistics? Are there any special programs within the DON that are already doing this? If so, does direct measurement yield greater insight into the contributions to logistics delays?

### 5.2.3 Accounting for the Shelf Life of Replacement Parts

On-board replacement parts can be stored on operational units for years before they are transferred or used during a maintenance action. Some parts have a shelf life where the part experiences a degradation in reliability. Spare parts containing batteries are examples of this situation. Within the DON, are there preexisting methods for assessing replacement part shelf-life? What is the best method for tracking these parts to ensure that operational units only retain reliable parts? Are these methods scalable to manage major weapon system programs containing thousands of unique replacement parts?

### 5.2.4 Time Periodicity for SOI Analysis

The analysis performed in the supplemental case study on CIWS assumes that an appropriate time interval to partition data is by fiscal year. This assumption allows for comparing case study results and those in the PEO RMA report. Most system RMA reports include performance metrics partitioned by fiscal year. Is a fiscal year the most appropriate time interval to partition data? It may be the case that the reliability of a system depends more on maintenance milestones than it does on time. For example, it might be more useful to investigate reliability and logistics metrics for a SOI from one major availability to another. This would mean that the time interval considered is a variable. The downside to not reporting metrics by fiscal year is that it makes cost-benefit analyses more difficult. However, partitioning the performance data in a way other than by fiscal year may help in better understanding the reliability and logistics characteristics of systems.

### 5.2.5 Part Refurbishment and Tracking

The CIWS case study identifies spare parts that go through a refurbishing process before being reintroduced back into circulation. Analysis of this part's reliability data shows an unpredictable failure rate from year to year. Are refurbished parts individually tracked to ensure that unreliable parts stay out of the supply chain? Additionally, how does the reliability of refurbished parts compare to new parts? Are spare parts being individually assessed for their reliability by tracking individual part serial numbers? Further investigation is required to determine why some refurbished parts appear to have different reliability characteristics compared to new parts.

### 5.2.6 Diagnosing Changes in Replacement Part Costs

This topic applies to any analysis that includes a cost-benefit analysis. The CIWS case study showed that replacement part costs have both significantly increased and decreased from FY14 to FY19. This observation means that a cost-benefit analysis has an inherent error due to the unpredictable part costs. A greater understanding of how major weapon system programs purchase spare parts and the driving factors for the variance in part cost would result in more accurate cost-benefit analyses.

## 5.3 Summary

This chapter summarizes the key findings of this thesis. Apparent capability gaps exist in the current ability to assess system readiness and efficiently diagnose system performance issues. This thesis recommends implementing the analysis method developed in Chapter 4 to efficiently diagnose system performance problems. This chapter also shows several more problems requiring attention to further develop this diagnostic method for DON systems. SOIs that operate at sea presents unique limitations to logistics delay improvements. As a result, this diagnostic method and future-work problems require tailored solutions to account for the operating environment.

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# CHAPTER 6: Supplemental

This chapter covers the supplemental material for this thesis. One supplemental document is given. Contact the NPS Dudley Knox Library for access to the supplemental case study.

## 6.1 Case Study of Close-In Weapon System

This supplemental case study applies the diagnostic method, given in Chapter 4, to the Close-In Weapon System (CIWS). Performance data from the MRDB on the CIWS is used to conduct the analysis. The case study addresses all steps of the diagnostic method and provides recommendations to the PEO IWS on potential COAs. System performance data from the MRDB is unclassified controlled information, FOUO, distribution statement D.

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